Blame it on the weather: Market implied weather volatility and firm performance *

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Abstract

We introduce a novel measure of weather risk implied from weather options' contracts. WIVOL captures risks of future temperature oscillations, increasing with climate uncertainty about physical events and regulatory policies. We find that idiosyncratic weather risk shocks worsen firms' operating performance and increase the uncertainty about firms' fundamentals, suggesting that firms, on average, do not fully hedge exposures to weather risk. We estimate returns' exposure to WIVOL innovations and show that more negatively exposed firms are valued at a discount, with investors demanding higher compensations to hold these stocks. Firms' exposure to local, but not foreign, WIVOL predicts returns, highlighting a new channel through which uncertainty shocks are priced locally.

JEL Classification: G11, G12, Q54

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1 Introduction

The link between financial markets and extreme events stemming from climate-related risks has been a topic of extensive discussion in both news and academic research. Whether these shocks arise from physical damages caused by extreme weather conditions or regulatory policies to transition to a less polluting economy, climate change is increasingly associated to the performance of various asset classes. If climate risks present material threats to firms' cash flows and stock prices, understanding firms' exposure to weather-related shocks becomes essential for investors and policymakers alike. This task, however, is challenging. Existing analyses rely heavily on firms' disclosures regarding their environmental policies, which are mostly voluntary and can be purposefully misleading, as noted by the Securities and Exchange Commission (SEC).[1] Furthermore, traditional metrics like average temperature fail to capture the full scope of temperature variability, presenting limitations in assessing the uncertainty and potential impacts of climate risks on economic outcomes.

In this paper, we employ a new perspective to examine risks associated with climate change. Rather than focusing only on ex-post extreme weather events, which are directional and seasonal in nature, we explore the relevance of ex-ante weather volatility risk for financial markets. Our primary interest is in understanding investors' expectations about future temperature fluctuations and the extent to which firms are exposed to this risk. We use weather option prices to estimate the time series for the implied weather volatility, since option contracts provide unique insights into investors' ex-ante beliefs on weather risk. The weather implied volatility (WIVOL) is estimated using weather option contracts traded at the Chicago Mercantile Exchange Group Inc. (CME), whose payoffs depend on daily devia-

[1] According to the SEC, few companies discuss about climate change and its more than a decade old guideline is in the process of being updated. Moreover, Morningstar notes that most companies do not disclose emissions data. See, for example, "SEC Opens Review of Corporate Climate Change Disclosures," Wall Street Journal, February 24, 2021; "SEC to Hunt for Climate-Friendly Marketing That Misleads Investors," Wall Street Journal, March 4, 2021; "Carbon Emissions Data for Investors: Closing the Reporting Gap and Future-Proofing Estimations," Morningstar Sustainalytics, February 8, 2023.

tions (or degree-days) in temperature from 65 degrees Fahrenheit.[2] To account for seasonal variations in temperature, the contracts are further classified into heating degree-days (HDD) and cooling degree-days (CDD) options. Intuitively, HDD measure the additional heating firms need to maintain normal operations in colder days during the winter months, and CDD measure the additional cooling firms need to maintain normal operations in warmer days during the summer months. From January 2005 to July 2021, we estimate WIVOL using option contracts written on temperatures recorded at the weather station of the LaGuardia airport and uncover significant fluctuations over time.

WIVOL exhibits varying patterns across different seasons and years, increasing at the onset of heightened uncertainty on physical and transition events. For example, WIVOL increases with the advent of Hurricane Sandy in 2012 but also during times of abnormally colder temperatures such as in early 2014 and 2021. WIVOL also changes with consistently higher than expected temperatures with no risk of physical damages. Notably, we report an upward shift in WIVOL around mid-2020, which coincides with increased concern from regulators about climate risks (see, for instance, Ramelli, Wagner, Zeckhauser and Ziegler (2021)). These findings suggest WIVOL seems to capture not only market expectations about physical risk events but also reflects the growing concerns about climate-related risks from federal agencies and policy makers.

Existing research illustrates that uncertainty diminishes the capacity of economic actors to strategize and operate efficiently, consequently leading to adverse effects on economic outcomes.[3] Weather risks can also significantly impact firms' operating performance. Unusual temperature patterns, such as warmer-than-normal summers or colder-than-normal winters, can result in unexpected operating costs due to heightened energy demand, disruptions in distribution channels, and decreased labor and capital productivity. Abnormal temperatures

[2]The 65F benchmark is based on industry conventions for commercial buildings' management and considered the most comfortable for normal operations.

[3]For example, gross domestic product is reduced by government spending volatility, and by exchange-rate volatility. Food price volatility also reduces agricultural output. Crop yields and human health are negatively affected by temperature volatility.

can influence local power plants, leading to service outages that add to the disruptions faced by these firms (Shive (2012)).[4] Higher chance of experiencing extreme temperatures also affects firms' performance by negatively impacting employees' mental and physical health, consequently affecting creativity, productivity and decision making abilities (Addoum, Ng and Ortiz-Bobea (2023)). Even less extreme temperature fluctuations pose a non-trivial risk for companies. For example, Hewlett Packard Enterprise's CEO Antonio Neri highlighted that HPE "projected scenarios for non-extreme weather events, finding than even small temperature increases (below 2 degrees Celsius) are important and could cost $200 million to the company".[5]

Therefore, using this novel measure of expected weather volatility, we study if idiosyncratic local risk shocks impact firms' value in equilibrium. Changes in expected oscillations in temperature measured by WIVOL offer a unique set of features to analyze firm performance under climate risk, as shocks to WIVOL are exogenous, local, idiosyncratic and unsystematic, as opposed to disasters type of extreme weather events with a potential systematic reach. We provide economic foundations to our empirical hypotheses with a dynamic model in which idiosyncratic weather volatility shocks impact firms' cash flows and stock returns. Following Merton (1987), we introduce a weather-specific risk component to the company's cash-flow process and show that investors demand an additional compensation to hold companies exposed to weather volatility.

In the theoretical framework, the value of the security is influenced by changes in expected temperature oscillations, measured by WIVOL, through two key channels. First, the firm's value is affected by the anticipated impact of WIVOL innovations on its future cash flows. The second channel addresses how weather-implied volatility affects the variance of the firm's

[4]Increased energy expenses for buildings could also substantially exacerbate higher operating costs. Heating, Ventilation, and Air Conditioning (HVAC) systems alone account for 38% of buildings' energy usage, with almost half of this consumption occurring in non-residential buildings (Gonzalez-Torres, Perez-Lombard, Coronel, Maestre and Da (2022)).

[5]"Companies' Climate Risks Are Often Unknown. Here's How One Opened Up," Wall Street Journal, March 14, 2021

operating performance. An increase in this second component decreases the security's value because higher discount rates are applied to future cash flows when calculating their present value. Consequently, investors require additional compensation to hold stocks of companies exposed to weather volatility, even if this volatility consists of idiosyncratic risk shocks, particularly when investors are unaware of the parameters governing the security's return process.

Our empirical analysis reveals that weather risk impacts firms' cash-flows and discount rates. Namely, higher weather implied volatility raises firms' operating costs and also heightens uncertainty about their fundamentals. We find that a one-standard deviation increase in ΔWIVOL results in a 4.4%, 4.8%, 1.4%, and 4.1% quarterly increase in the absolute changes of the firms' revenue, cost of goods sold, SG&A expenses, and the total operating expense, respectively. Additionally, our findings document a tendency among managers to shift investors' focus towards firms' vulnerability to climate change risks. This inclination becomes evident when WIVOL shocks increase firms future operating costs but also managers' discussions on weather risks, as they seem to *blame it on the weather* and attribute these challenges to weather-related events.

We then utilize WIVOL to examine how firms' equity prices are influenced by market expectations of weather risk. Specifically, we estimate the exposure (betas) of firms to innovations in WIVOL and analyze their predictive power for these firms' future performance. The underlying hypothesis is that firms with more negative exposure to WIVOL innovations are valued at a discount. The reasoning behind this is that if expectations of larger temperature fluctuations lead to a higher risk of unexpected costs for the company, then forward-looking investors might demand compensation for holding stocks with more negative WIVOL beta. Consequently, this gives rise to a negative relationship between a firm's beta and its future stock return. To assess the significance of weather volatility risk, we conduct our empirical analysis using the set of firms headquartered in the city of New York.

We examine the predictive power of WIVOL beta on stock returns by forming portfolios based on stocks' betas from the previous month. Using a long-short strategy that buys stocks with the most negative WIVOL betas and sells those with the most positive, we achieve risk-adjusted annualized returns ranging from 7.6% and 9.1%. We also assess the impact of WIVOL beta at the individual firm level using Fama-MacBeth regressions, finding a significant negative relation between firms' betas and their future stock returns. This return predictability remains robust even when excluding financial sector firms or expanding the sample to include firms headquartered within 100 miles of LaGuardia Airport. Moreover, we test and confirm that it is the uncertainty about future temperature fluctuations, rather than expectations of future temperature, what seems to impact firms' performance.[6]

To investigate on the underlying mechanism driving return predictability, and guided by the theoretical implications of the model, we then conjecture that firms with higher informational friction costs will experience stronger performance in long-short strategies based on WIVOL beta. Using various proxies for information friction, such as institutional holdings and local ownership, we find that abnormal returns are significant for stocks with low institutional holdings and high local ownership. Additionally, firms with greater exposure to local discount rate shocks, such as those with substantial local operational presence and labor productivity growth, show stronger WIVOL beta effects. We further examine firm profitability and observe significant abnormal returns within more profitable firms, indicating that financial constraints are not the primary driver of these results. Instead, information frictions and sensitivity to local discount rate shocks play a key role in how WIVOL beta predicts local stock returns.

Overall, given that stock prices are determined by ex-ante discounted cash-flows, these

[6] It is worth noting that strategies hedging climate risk are largely based on signals derived from extreme weather events, which are more likely to be associated with the summer months (e.g., extreme heatwaves, hurricanes). In light of this, we investigate if the performance of the WIVOL beta strategy is actually, and only, a summer affair. One of the advantages of the WIVOL beta strategy is that it does not depend on the occurrence of extreme events that are likely seasonal and infrequent. After computing average returns for each month of the year using the beta long-short strategy, our analysis confirms that the performance of the WIVOL beta strategy is not limited to the summer months.

results suggest that the option implied weather volatility contains value-relevant information that is not encompassed by historical counterparts. By extracting expectations of future weather volatility, as opposed to relying on realized ex-post equivalent measures, investors can more effectively gauge the extent of firms' susceptibility to weather risks. Importantly, our results highlight the role of informational frictions in asset pricing, with stronger return predictability observed among firms facing higher costs related to information acquisition and investor recognition, rather than financial constraints.

Finally, and given that WIVOL is a geographic based measure, we expect local firms to exhibit stronger exposure than non-local firms based in a different state. To explore the local aspect of WIVOL, we estimate the option implied volatility of weather for the Dallas-Fort-Worth metroplex, with temperatures recorded at the weather station in the Dallas Fort-Worth International airport. We find that, as in the case of New York, firms based in the Dallas Fort-Worth area are significantly exposed to innovations in the WIVOL of Dallas Forth-Worth. Greater negative exposure of firms to WIVOL predicts higher future returns, validating our initial hypothesis. Interestingly, our second set of results confirm the local nature of weather risks. When we estimate New York firms' betas with respect to innovations in the WIVOL of Dallas Fort-Worth, the predictability of these betas is statistically insignificant. Likewise, estimating Dallas Fort-Worth based firms' exposure to innovations in the WIVOL of New York leads to no predictability of future returns. This outcome indicates that firms are indeed significantly exposed to uncertainty about weather volatility risks specific to the city in which they are based.

The structure of the papers is as follows. Section 2 discusses the literature related to the paper. Section 3 presents the main data sets used in the analysis. Section 4 presents the weather option implied volatility (WIVOL). Section 5 discusses the empirical results. Section 6 concludes.

2 Related Literature

While the topic on the interactions between climate events and financial markets is relatively new, there has been a great amount of interest and research in the field. Giglio, Kelly and Stroebel (2021) and Hong, Karolyi and Scheinkman (2020) provide an excellent review on this literature.[7] We next describe the studies most related to our work and then discuss our contribution.

A growing literature investigates the exposure of different asset classes to climate risks. The asset classes include stocks, municipal and corporate bonds and real estate, while the climate risks considered are physical risks, transition risks or a combination of both. To determine the variable of interest governing these risks dynamics, the literature uses text-based techniques (e.g., financial statements, news articles, emissions disclosures) or historical extreme events (e.g., extreme heat, hurricanes, sea level rise).

In equity markets, several studies find substantial effects of climate risk on investors' decisions and asset returns. Engle, Giglio, Kelly, Lee and Stroebel (2020) develop a text-based index using climate change news from the Wall Street Journal and find that ESG friendly stocks outperform with news coverage. Choi, Gao and Jiang (2020) use Google news search to find that, when temperature levels are abnormally high, investors pay more attention to global warming and stocks disclosing high levels of CO2 emissions underperform. Bolton and Kacperczyk (2021) use firms' voluntary disclosures of CO2 emissions and document that more polluting firms earn higher future returns, as they are more exposed to regulatory risks, and consistent with the findings of Hsu, Li and Tsou (2023). Alekseev, Giglio, Maingi, Selgrad and Stroebel (2022) combine extreme heat shocks with managers' SEC disclosures to determine the stocks to buy and sell. Bansal, Kiku and Ochoa (2019) document that low-frequency variations in temperature carry a positive risk premium. Sautner, van Lent,

[7]With regards to the measurement of climate related risk exposure, the traditional keywords in the literature are global, aggregate, slow-moving, extreme, directional, objective (ex-post), emission, and rating based. However, the keywords in this paper are local, dynamic updates, arrival of information, uncertainty or bi-directional, non-extreme inclusive, belief (ex-ante), and priced based.

Vilkov and Zhang (2023) also develop a text-based approach to determine firms' exposure to climate change based on managers earnings calls disclosures.

Climate risk also affects financial assets beyond equities. In options markets, Ilhan, Sautner and Vilkov (2021) find that the cost of option protection against downside tail risk is larger for firms with more carbon-intense business models. Kruttli, Roth Tran and Watugala (2023) document that firms in a landfall region exhibit large, long-lasting increases in implied volatility reflecting not only landfall uncertainty but also impact uncertainty. In fixed income markets, studies have shown that physical climate risk such as heat stress and sea-level rise is priced in municipal bonds market (e.g., Painter (2020), Acharya, Johnson, Sundaresan and Tomunen (2022) and Goldsmith-Pinkham, Gustafson, Lewis and Schwert (2023)).[8] In housing and mortgage markets, many of the researchers find empirical evidence that physical climate risk such as rising sea levels, hurricane and wildfires, directly affect real estate prices since the value of real estate is tightly linked to the value of the land it is build on (e.g., Hauer, Evans and Mishra (2016), Murfin and Spiegel (2020), Bernstein, Gustafson and Lewis (2019)).[9]

This paper complements previous empirical findings on the impact of climate risk on economic fundamentals. For example, Baker, Bloom and Terry (2023) use natural disasters around the world as an instrument for the second moment shocks and reveal a negative impact of uncertainty on growth. Pankratz, Bauer and Derwall (2023) and Addoum, Ng and Ortiz-Bobea (2023) examine the impact of extreme temperatures on individual firms' and industries' operating performance, respectively. Extreme temperatures also reduce labor working hours (Graff Zivin and Neidell (2014)) and labor productivity in heat sensitive sectors (Somanathan, Somanathan, Sudarshan and Tewari (2021)). Barrot and Sauvagnat (2016) show that natural disaster shocks to suppliers propagate in production network by

[8]Huynh and Xia (2021) document that corporate bonds with positive covariance with a climate news index have lower average returns.

[9]Investors' attention and local beliefs in climate change can also play an important role (e.g., Baldauf, Garlappi and Yannelis (2020) and Giglio, Maggiori, Rao, Stroebel and Weber (2021)).

imposing permanent output losses on their customer firms. More broadly, our findings support for papers documenting economic, financial or political uncertainty-averse investors demand extra compensation to hold stocks exposed to those uncertainty shocks (Bali, Brown and Tang (2017), Baker, Bloom and Davis (2016) and Kelly, Pastor and Veronesi (2016)).

Our study also contributes to literature studying the weather derivatives market. Purnanandam and Weagley (2016) show that the introduction of weather derivatives contracts improve the accuracy of temperature measurement at the underlying weather stations. Weagley (2018) emphasis that financial sector's risk sharing capacity affects price movements of weather derivative contracts. Perez-Gonzales and Yun (2013) and Armstrong, Glaeser and Huang (2022) present empirical evidence that active risk management policies following the introduction of weather derivatives lead to increase in firm value and decrease in corporate executive compensation, respectively. Schlenker and Taylor (2021) show that prices of weather derivatives predict future temperatures better than existing climate models.[10]

Overall, this paper makes the following contributions to the literature on climate risk. First, instead of extreme weather risk, we study the impact of innovations to temperature volatility on firms. We find that a rise in weather uncertainty increases the probability of experiencing temperatures colder than expected in winter or warmer than expected in summer, resulting in unforeseen costs for the firm and ultimately impacting its performance. Second, we introduce a novel measure of weather risk by estimating the time series for the volatility of temperature implied by weather option prices. We find that firms with more positively exposed to innovations to the weather implied volatility exhibit lower expected returns. Third, we study, and confirm, the local nature of weather volatility. We find that firms are exposed to the volatility of weather in the area in which they are based only, a result that highlights the importance in distinguishing between global and local weather risk.

[10] Our paper differs, but complements, the findings from Bae et al. (2024), which highlight the informativeness of weather derivatives as an important factor in explaining the credit spreads of municipalities.

3 Data and Methodologies

We obtain data on weather derivatives from the Chicago Mercantile Exchange Group Incorporated (CME). CME weather derivatives are exchange-traded contracts whose payoff depends on the evolution of a weather-related variable for a specific geographic location and period of time. The contracts are in the form of futures and options on futures, while the weather variable is an index based on daily temperature.[11] We next define the variables used in the computation of the derivatives' payoff.

The daily temperature (in Fahrenheit degrees) is measured for a specific weather station and the weather index is in degree-days, which is the daily temperature deviation from 65 Fahrenheit degrees. We consider two degree-days cases. Heating degree-days (HDD) measures the deviation below 65 degrees, while cooling degree-days (CDD) measures the deviation above 65 degrees. Intuitively, HDD measure the additional heating firms need to maintain normal operations during colder days (below 65F). CDD measure the additional cooling firms need to maintain normal operations during warmer days (over 65F).

Option contracts written on futures contracts are based on the degree-days index, and so is their strike price. The futures contracts are written on the cumulative degrees days over a specific period of time. HDD call and put options payoff with strike price K and with T days to maturity respectively take the form

$$C_T^{HDD} = \max\left(\sum_{t=1}^{T} \max\left(65 - F_t, 0\right) - K, 0\right) \tag{1}$$

$$P_T^{HDD} = \max\left(K - \sum_{t=1}^{T} \max\left(65 - F_t, 0\right), 0\right) \tag{2}$$

Likewise, CDD call and put options payoff with strike price K and with T days to maturity

[11] Alternative weather variables include rainfall, snowfall and frost.

respectively take the form

$$C_T^{CDD} = \max\left(\sum_{t=1}^{T} \max\left(F_t - 65, 0\right) - K, 0\right) \tag{3}$$

$$P_T^{CDD} = \max\left(K - \sum_{t=1}^{T} \max\left(F_t - 65, 0\right), 0\right) \tag{4}$$

We focus on monthly HDD and CDD contracts, for which both futures and options on futures expire on the second business day after the futures contract month. The CME lists HDD contracts for the months of November, December, January, February and March plus the transition months of October and April. CDD contracts are listed for the months of May, June, July, August and September plus the transition months of October and April. For each trading day, we collect data on the contract expiration date, option price, futures price, strike price and option implied volatility. Using these inputs and U.S. Treasury bill rates, we confirm the contracts' option implied volatility following Black (1976) and discard observations violating the put-call parity and outside the 0-200 percent range (see, for example, Goyal and Saretto (2009) and Chabi-Yo, Doshi and Zurita (2023)).

To study market expectations of localized weather volatility, we focus our analysis on future weather oscillations for the city of New York given that it represents the most liquid contract (Schlenker and Taylor (2021)). Therefore, the degree-days are with respect to the Weather Bureau Army station located at the LaGuardia airport (WBAN 14732). In order to generate a time series for the monthly weather option implied volatility, we utilize option contracts that are at-the-money and with maturity closest to 30 days. In addition, we compute the average implied volatility between HDD and CDD contracts for the transition months of October and April. We follow this procedure for each day from January 2, 2005 to July 31, 2021, and then take the monthly average. The resulting variable is the one-month, at-the-money, weather option implied volatility (WIVOL) that we discuss in next Section.

Data with respect to firms' is obtained from CRSP, Compustat and Optionmetrics. We collect monthly observations on firms' stock price, market capitalization and corporate headquarter location (matching the firm's city, state and zip code) from CRSP. We collect quarterly accounting data from Compustat. For the period between January 2005 to July 2021, the sample contains 2,386 New York based firms, with an average (median) of 833 (790) firms per month. We discard stocks with a price per share less than $5 and firms with less than 24 monthly returns. Table 1 reports the summary statistics for WIVOL innovations (monthly changes) and quarterly firm-level characteristics.

[Insert Table 1 Here]

4 Weather Option Implied Volatility

Figure 1 plots the time series for WIVOL, the weather option implied volatility based on the temperature recorded at the LaGuardia airport in the city New York. The sample period is from January 2005 to July 2021. To construct the time series, we use closest to one month to maturity option contracts that are at-the-money. The time series reports the average monthly observation from daily traded contracts. The series exhibits an average of 26.1% (median of 23%) implied volatility of weather throughout the sample.

[Insert Figure 1 Here]

The time series exhibits substantial time variation. WIVOL, given its link to the second distributional moment of a random variable, captures expected future oscillations due to both large and small shocks. We observe major oscillations in times of uncertainty about hurricanes in the summer season and snowstorms in the winter season. In 2005, while New York was not directly impacted by major developments in the Atlantic ocean, including Hurricane Katrina, local weather developments impacted WIVOL. June of 2005 was designated the warmest June on record, with WIVOL reaching 58%. October 2005 was the wettest month on record, with almost double the amount of rain recorded in any October and causing local flooding. WIVOL climbed to 52.9%.

In 2010, WIVOL peaked to 80.4% for what would end up being New York's hottest summer on record. Interestingly, in this record-breaking season there was no cataclysm that defined the period but a consistently higher than expected temperature. A combination of record breaking heat combined with a strong backdoor cold front approaching the region from the northeast helped to provide a very unstable environment. Flooding disrupted New England, with stretches of Interstate 95, the main route linking Boston to New York, closed for days. Hurricane Earl generated most of the uncertainty in October 2010 but ultimately did not impact the area. However, the city Power Authority was criticized for excessive spending on emergency crews, which led increased power rates for New York buildings.

WIVOL reached its maximum value of 81.7% in September of 2012, preceding the arrival of hurricane Sandy in the following month. Large parts of the city and surrounding areas lost electricity for several days as a result of the storm, which killed 43 people in New York City. Rehse, Riordan, Rottke and Zietz (2019) document that increased uncertainty about material physical risks like the impact of Hurricane Sandy lowers market liquidity. The winter of 2014 also generated an increase in WIVOL, with utilities asking customers to cut power use in early January and natural gas prices soaring as a snowstorm brought freezing temperatures to the northeast of the country.

We continue to observe time variation throughout the sample, with an upward shift in mid-2020. The increase in WIVOL can be related to climate policies and regulations for the city, as the New York State Department of Financial Services urged New York-based insurance companies to better manage the risks they face from climate change.[12] Moreover, the agency states that it would start asking insurers in 2021 what steps they have taken as part of its examination process. This local policy event, combined with discussions at the federal level regarding a stronger stance from regulators towards climate change could have

[12] "New York Regulator Pushes Insurers on Climate Change," Wall Street Journal, September 22, 2020.

impacted WIVOL given the increased demand for hedging climate risks.[13] In 2021, WIVOL drastic increase in February of 2021 is consistent with local and national weather events during this month, the latter mostly driven by the Texas power crisis caused by the winter storm. New York experienced one of the snowiest Februaries on record, with the National Weather Service registering three significant weather events for New York. Winter weather emergency declaration restricted all non-emergency travel in early February as well as all flights cancellation in LaGuardia airport.

When we contrast WIVOL with other risks measures, the findings suggests it is related to weather specific risks, which are location specific in nature. Table 2 reports results from time-series regressions in which the change in the weather option implied volatility, WIVOL, is regressed on various variables including the climate change news index from Engle, Giglio, Kelly, Lee and Stroebel (2020), the intermediary capital ratio and intermediary risk factor of He, Kelly, and Manela (2017), the change in the political uncertainty index from Baker, Bloom, and Davis (2016), the change in financial, macro, and real uncertainty of Jurado, Ludvigson, and Ng (2015), and the change in the implied volatility of the S&P 500 index. We find that WIVOL is not statistically significantly associated with climate change news and proxies of macro and financial uncertainties, and intermediary capital constraints.[14] The lack of significance suggests that the dynamic of WIVOL is not mainly driven by capital constraints of financial institutions, nor is it driven by other financial and macro uncertainties. Instead, it is guided by weather uncertainty, which arises exogenously from the financial markets.

[Insert Table 2 Here]

Overall, we observe that WIVOL seems to capture future temperature oscillations, with

[13]A recent survey by Stroebel and Wurgler (2021) finds that investors identify regulatory risk as the most important climate risk to business in the short-term.

[14]The coefficients on WIVOL is also statistically insignificant for other variables including the total new privately owned housing starts, the change in term spread, the change in the civilian unemployment rate, and the price-earnings ratio and the return of the S&P 500 index.

peaks before or at the onset of important physical weather risks. It also seems to be related to regulatory or transition risks, as the increased levels from the mid-2020 suggests.

5 Weather Volatility and Asset Pricing

In this section, we investigate the relevance of weather volatility shocks for firms' cash-flows and expected returns. We first motivate the empirical analysis by discussing the main results of the dynamic model derived in the Appendix, where idiosyncratic weather risk impacts firms' value in equilibrium.

Classical work of Sharpe (1964) and Lintner (1965) predicts that variables other than the market factor exposure do not affect security prices. Merton (1987) deviates from standard asset pricing models and demonstrates that idiosyncratic risk can be priced in equilibrium if some investors are underdiversified and do not hold the market portfolio. In the same vein, our model features a Merton (1987) economy with the firm's cash-flows subject to systematic and unsystematic risk. We introduce an idiosyncratic, locally sourced climate risk friction into an otherwise friction-less economy and show that weather risk shocks impact operating performance and expected returns in equilibrium. Weather risk shocks lower firms' market value by decreasing cash flows while increasing discount rates, and ultimately increase expected returns.

In a friction-less economy, firm k value V_k^* is subject to only a systematic common factor risk. The introduction of an idiosyncratic weather risk component σ_k^2 into the firm's cash-flow will alter its value to V_k. In the Appendix, we show that the presence of weather risk lowers firm value V_k compared to the standard case V_k^*

$$V_k = \frac{V_k^*}{1 + \left[(\varphi_k^2 + \sigma_k^2)\frac{(1-q_k)x_k\delta}{q_k R_f}\right]} \tag{5}$$

The presence of idiosyncratic weather risk σ_k^2 increases expected excess returns

$$E(\widetilde{R}_k) - R_f = \eta_k \eta \delta + \frac{\delta x_k(\varphi_k^2 + \sigma_k^2)}{q_k} \tag{6}$$

with η, φ, q, x, and δ defined in the Appendix.

In the following sections, we study whether shocks to idiosyncratic weather volatility are priced. Weather risk shocks are local and idiosyncratic in nature. For example, an increase in expected oscillations in temperature for the city of New York is likely to be of more importance for the operating performance of firms based in the city of New York than in the city of Dallas. Moreover, changes in expected oscillations in temperature measured by WIVOL offer a unique set of features to analyze firm performance under climate risk, as shocks to WIVOL are exogenous, local, idiosyncratic and unsystematic, as opposed to disasters type of extreme weather events with a potential systematic reach.

5.1 WIVOL and Operating Performance

Weather is considered a key driver for buildings' energy consumption since it affects energy demand for heating, ventilation, and air conditioning (HVAC). Furthermore, other weather dependent conditions, such as daylight and humidity have a great impact on the use of equipment and on the number of hours indoors (Gonzalez-Torres, Perez-Lombard, Coronel, Maestre and Da (2022)). In the U.S., large office buildings account for 65% of the total electricity use and 36% of total energy use, with heating and cooling building services generating 15% of worldwide greenhouse-gas emissions. Larger oscillations in temperature around normal levels can therefore have non-trivial effects on firms' cash-flows. And this also includes non-disaster events.

Given that WIVOL measures expectations of future temperature oscillations around normal levels, we study the extent to which firms' operating performance is impacted by innovations to WIVOL. Weather risk can directly impact firms, as temperatures outside the normal range increases operating costs due to higher demand for energy. But it also does it indirectly, impacting power plants in the area which during outages cannot supply services to these firms, creating further disruptions (Shive (2012)). To implement our empirical analysis, we obtain firm-level data from Compustat. Following Petersen (2009), we implement quarterly panel predictive regressions where the dependent variables are various proxies form firm-level operating costs and revenue. The main explanatory variable is lagged quarterly innovations in WIVOL. We use as control variables the logarithm of the firm's market capitalization (*Size*), the book-to-market ratio (*Book-to-Market*), the gross profitability (*Profitability*) as in Novy-Marx (2013), the logarithm of the number of months since a listing date (*Age*), the book leverage (*Leverage*) defined as short- and long-term debt, scaled by the total debts and common equity, the average number of shares traded over the previous three months scaled by shares outstanding (*Share Volume*), the logarithm of the price (*Price*), the cumulated past performance in the previous year by skipping the most recent month (*Momentum*), and the earnings to price ratio (*Earnings-to-Price*). We compute t-statistics controlling for firm and year fixed effect and clustering standard errors at the firm level to account for potential serial correlation in the residuals. Table 3 presents the panel regression results.

[Insert Table 3 Here]

For the proxies of operating costs, we use the logarithm of the cost of goods sold (Column 1), selling, general and administrative expense (Column 2), total operating expense (Column 3) and inventory costs (Column 4). The coefficients for ΔWIVOL are positive and statistically significant for all four proxies, indicating that positive innovations to WIVOL lead to higher operating costs in the following quarter. The economic significance is high: a one-standard deviation increase in ΔWIVOL results in a 0.45% increase in the level of total operating costs. This finding is consistent with Somanathan, Somanathan, Sudarshan and Tewari (2021), who show that temperatures outside expected intervals can generate unexpected costs. WIVOL measures precisely the risk of temperatures falling below 65 degrees Fahrenheit in the winter months or exceeding 65F degrees in the summer months, with the 65 figure based on industry conventions for normal building operations. Addoum, Ng and Ortiz-Bobea (2020) find that extreme weather events have insignificant effects on firms' establishment sales, suggesting that large corporations have the resources to withstand physical damages. In the case of firms' exposure to innovations in WIVOL, these shocks include also non-extreme events that can still impact firms due to unexpected operational costs. In column 5 and 6, we further investigate the effect of the weather implied volatility on the firms' revenue and earnings forecasts and report that innovations to WIVOL have no significant effect on firms' sales but negatively impact analysts' earnings estimate for the next fiscal quarter, scaled by lagged stock price. These results on the relevance of weather shocks are consistent with Brown, Gustafson and Ivanov (2021), who document that severe winter weather has no impact on firms' sales but reduces firms' cash-flows by increasing operating costs. Unlike severe winter weather shocks, WIVOL innovations encompass both extreme and non-extreme events and seem to be prevalent during all seasons.

5.2 WIVOL and Fundamental Uncertainties

In the theoretical framework, the value of the security is influenced by changes in expected temperature oscillations measured by WIVOL through two key components. First, the firm's value is affected by the anticipated impact of changes in WIVOL on its future cash flows. The second component addresses how weather-implied volatility affects the variance in the firm's operating performance. An increase in this second component decreases the security's value because higher discount rates are applied to future cash flows when calculating their present value. Consequently, investors require additional compensation to hold stocks of companies exposed to weather volatility, even if the volatility consists of idiosyncratic shocks, particularly when investors are unaware of the parameters that govern the security's return process. In this section, we explore whether the changes in WIVOL has a meaningful impact on the firms' fundamental uncertainties.

In Table 4, we report the emprical results from the panel regression investigating the effect of the weather implied volatility on the firms' fundamental uncertainties. The firms' fundamental uncertainties are measured by taking the absolute values of the quarterly changes in the following values: the firm's revenue (column 1), the cost of goods sold (column 2), the selling, general, and administrative expense (column 3), and the total operating expense (column 4). All four variables are scaled by the last quarter's total asset.

[Insert Table 4]

The panel regression results show that the coefficients for ΔWIVOL are positive and statistically significant for all four proxies, indicating that positive innovations to WIVOL not only lead to higher operating costs but also higher uncertainties in those values in the following quarter. Economically, a one-standard deviation increase in ΔWIVOL results in a 4.4%, 4.8%, 1.4%, and 4.1% increase in the absolute changes in the revenue, the cost of goods sold, the general and administrative expense, and the total operating expense, respectively. These results are in line with Irvine and Pontiff (2009), who document that higher volatility of fundamental cash flows is linked to higher idiosyncratic volatility, and with Wei and Zhang (2006), who report that idiosyncratic volatility is linked to a decrease in corporate earnings and an increase in earnings volatility.

Beyond the uncertainty measures based on accounting statements, we also investigate the effect of the weather implied volatility on other proxies of the firms' fundamental uncertainties. First, we explore whether managers tend to blame firms' prospective poor performance on the weather. The significant effect of weather volatility on firms' future costs and uncertainties associated with those suggest that managers should consider this risk as non-trivial.

To investigate this matter, we analyze the relevance of WIVOL on managers' discussions concerning risk associated with the climate change during firms' upcoming earnings calls. We employ the company-level measure of exposure to climate change risk developed by Sautner, van Lent, Vilkov and Zhang (2023) as a proxy for the level of attention managers dedicate to climate change risk. We anticipate that positive shocks to WIVOL will lead to an increase in discussions about climate change risk in the future. This mirrors the case observed when considering the firm's operating cost and its uncertainty.

Note that this analysis examines whether there is an increased focus from managers about firms' climate change exposure subsequent to positive shocks to the WIVOL metric, regardless of whether these managers implement policies to mitigate the said exposure. In Table 5, columns 1 and 2 show that innovations to WIVOL result in increased discussions about climate change risk among managers and greater earnings surprises for firms, respectively. [15] The results imply that, following an episode of weather-related uncertainty shock, managers redirect the attention of investors toward their firms' susceptibility to risks arising from climate uncertainty. This is a means to explain the negative repercussions of these shocks on the companies' fundamentals in the future. This pattern also suggests that managers attribute potential underperformance of the firm to the impact of uncertainty stemming from weather shocks, thereby safeguarding their own professional standing.

[Insert Table 5 Here]

Furthermore, we analyze the response of option traders by examining the first difference of call option implied volatility with 30 days of maturity and delta of 0.5 (column 3), the first difference of put option implied volatility with 30 days of maturity and delta of -0.5 (column 4), and the implied volatility of put option with moneyness closest to but above 1 minus that of call option with moneyness closest to but below 1 (column 5) of Table 5. These results

[15] We compute standardized earnings surprises by subtracting the mean analyst expected earnings from the actual earnings and then scaling by the standard deviation of the analyst forecasts.

suggest that option traders react positively to news of positive shocks to weather uncertainty by increasing the prices of both call and put equity options. Notably, the price increase is more pronounced for put options, leading to higher skewness in the equity option market following the positive weather uncertainty shocks.

Taken together, the results in this section confirm our hypothesis that an increase in market expectations about future temperature volatility leads to an increase in firms' operating costs and uncertainties associated with those fundamentals, with managers acknowledging the importance of weather risks. In Table A.1 in the appendix, we also show that our baseline results are not driven by a particular sector by adding an sector-specific interaction term.[16]

5.3 Firm-level Exposure and Expected Returns

Having established that idiosyncratic weather risk shocks not only lead to higher operating costs but also higher uncertainties in those values, an implication derived from the model's first order conditions, we next study if weather risk exposure is priced in the cross section of expected returns. Weather risk shocks, proxied by innovations to WIVOL, provide a unique set of features to study climate risk and stock returns, given their local, exogenous and unsystematic nature.

Do firms' exposures (betas) to innovations in WIVOL help predict these firms' future returns? Intuitively, firms with more negative exposure to weather risks will perform poorly as WIVOL increases, and therefore investors demand a higher compensation to invest in these firms. Conversely, firms with more positive exposure provide a good hedge against weather risks, and therefore investors are willing to pay higher prices and accept lower future returns for them. If this reasoning manifests over time, then a strategy buying stocks with most negative exposure while selling stocks with most positive exposure will exhibit positive and statistically significant returns.

[16] We analyze the manufacturing, transportation, wholesale, retail, finance and service sectors based on firms' SIC numbers.

We thus estimate the exposure of firms to weather option implied volatility innovations. Specifically, each month t and for each firm i, we estimate the $\beta^{\Delta WIVOL}$ of individual stocks using monthly rolling regressions of excess stock returns on ΔWIVOL

$$R_{i,t} = \alpha_{i,t} + \beta_{i,t}^{\Delta WIVOL} \Delta WIVOL_t + \beta_{i,t}^{X} X_t + \varepsilon_{i,t} \tag{7}$$

where $R_{i,t}$ is the excess return of firm i in month t, ΔWIVOL is the innovation in weather option implied volatility and X is a set of controls. The controls impose for the loading $\beta^{\Delta WIVOL}$ to be orthogonal to the stock market excess return and the historical temperature volatility.[17] We use a 36-month window in the estimation of $\beta^{\Delta WIVOL}$. The first set of betas are obtained using the sample from January 2005 to December 2007. We then use these monthly betas to predict stock returns in the following month (January 2008) and repeat this exercise until July 2021.

To construct the long-short strategy, we form quintile portfolios by sorting individual stocks based on their previous-month betas. The portfolio quintile 5 (high) contains stocks with the highest (most positive) $\beta^{\Delta WIVOL}$ during the previous month, while the portfolio quintile 1 (low) contains stocks with the lowest (most negative) $\beta^{\Delta WIVOL}$ during the previous month. The difference portfolio (low minus high) results from holding a long position in the low $\beta^{\Delta WIVOL}$ portfolio and a short position in the high $\beta^{\Delta WIVOL}$ portfolio. We implement and rebalance the long-short strategy on a monthly basis and for the sample period from January 2008 to July 2021. Table 6 reports the results for value-weighted portfolios. Specifically, the Table reports the average betas as well as annual raw returns and abnormal returns for each quintile portfolio and long-short strategy. By construction, since the portfolios are formed by ranking stocks on previous month exposures, quintile betas monotonically decrease from 0.29 for portfolio 5 to -0.37 for portfolio 1. For the long-short strategy, the

[17] We proxy for the historical volatility of temperature with the standard deviation of the year-over-year change in temperature in the last 36 months. Using alternative definitions for the computation of the historical volatility produces similar results. The historical volatility is based on NOAA daily temperatures for the LaGuardia airport.

average return difference between quintile 1 (Low) and quintile 5 (High) is statistically significant and equal to 0.72% per month with a five-lags Newey and West (1987) corrected t-statistic of 2.44. This result indicates that stocks in the lowest beta quintile generate 8.76% higher annual returns compared to stocks in the highest beta quintile.

[Insert Table 6 Here]

We investigate the possibility that return predictability generated by $\beta^{\Delta WIVOL}$ decreases once we incorporate well established risk factors. We therefore account for the excess market return, the three factors of Fama and French (1994), the Carhart (1997) momentum factor, the five factors of Fama and French (2015) and the four factors of Hou, Xue and Zhang (2014). In columns 3 to 7 of Table 6, each entry reports the intercept (alpha) from the regression of the portfolio returns on a constant and a risk factor model. In all cases, the long-short strategy yields economically and statistically significant returns, with alphas ranging from 7.68% to 9.12% annual, even after controlling for different risk factors.

These results suggest that sorting equity portfolios based on firms exposure to WIVOL innovations seems to provide significantly positive returns. In addition, the $\beta^{\Delta WIVOL}$ strategy provides diversification benefits, given the correlation between WIVOL and VIX and the global warming news index from Engle, Giglio, Kelly, Lee and Stroebel (2020), as we document in Section 4. Strategies that hedge climate risks based on extreme events can be challenging to rebalance frequently. This is the case since extreme events can be rare and also seasonal, such as the case of extreme hot temperatures or hurricanes, usually during the summer months. Firms, however, are exposed to uncertainty about temperature volatility year-round. The long-short $\beta^{\Delta WIVOL}$ strategy provides an alternative that can be implemented every month of the year. However, a valid concern is if the $\beta^{\Delta WIVOL}$ strategy is a summer affair. If its performance is mostly driven by extreme, seasonal events during the summer, we expect for its return to originate mostly in the summer months. To test this hypothesis, we compute the average return for each month of the year during our sample.

Figure 2 confirms that the performance of the strategy is not a summer affair, with December (106 monthly basis points) representing the month with largest return, followed by the month of April (86 monthly basis points).

[Insert Figure 2 Here]

We further look into the return effect of $\beta^{\Delta WIVOL}$ at the individual instead of portfolio level. We examine the cross-sectional relation between expected returns and lagged betas at the stock level using Fama and MacBeth (1973) regressions. We compute the time-series averages of the slope coefficients from the regressions of one-month-ahead stock returns on the beta. The average slopes provide standard Fama-MacBeth tests for determining if the explanatory variable has, on average, nonzero premium. Table 7 reports the time-series averages of the slope coefficients and the Newey-West t-statistics in parentheses. The univariate regression results reported in column 1 indicate a negative and statistically significant relation between the beta and the cross-section of future stock returns. From columns 2 to 8, we sequentially incorporate firm characteristics in the regression as control variables, which are well-documented in the literature as being associated with future stock returns. These characteristics include firm size (logarithm of market capitalization), cash flow levels, profitability, leverage, investment, book-to-market ratios, and Altman's z-score. Consistent with the portfolio-level findings, firms with lower $\beta^{\Delta WIVOL}$ are robustly associated with higher future returns. Sautner, van Lent, Vilkov and Zhang (2023b) document that managers discussions on climate change do not seem to predict the realized future return of these firms. Their non-result could be an indication that, despite managers' discussing on climate change, they seem to *blame it on the weather* instead of implementing hedging policies. This is also consistent with the significant return effect of $\beta^{\Delta WIVOL}$, since its relevance suggests that managers do not fully hedge weather risk exposure.

[Insert Table 7 Here]

We conduct several robustness checks in our analysis. Initially, we investigate alternative specifications concerning firm-level exposure to weather uncertainty shocks. Specifically, in Table A.2, we recalibrate each firm's beta, as defined in equation 7, employing various sets of controls: without any controls (Panel A), with control for the market factor MKT (Panel B), and with control for historical weather volatility (Panel C). Notably, we observe statistically significant average return disparities between quintile 1 (Low) and quintile 5 (High) across all three specifications. Correspondingly, in Table A.3, employing cross-sectional regressions, we find persistent robustness in the significance of the beta return effect. Subsequently, we exclude firms within the financial sector, as determined by their SIC code (60-67 Finance, Insurance, and Real Estate), and construct quintile portfolios based on the previous month's $\beta^{\Delta WIVOL}$. Table A.4 demonstrates that our long-short strategy yields economically and statistically significant returns, with alphas ranging from 12.36% to 15.84% annually after accounting for various risk factors. In another robustness check, we broaden our selection criteria beyond firms based solely in New York City, opting instead for firms headquartered within 100 miles from LaGuardia airport. The results in Table A.5 reinforce the robustness of our empirical findings.

We also look into whether return predictability arises from exposure to first order shocks instead of volatility shocks. To this end, we use historical, forecasted and traded proxies for temperature shocks. The first proxy is the monthly historical percentage changes in temperature recorded by the NOAA program. For the second proxy, temperature forecast, we follow Schlenker and Taylor (2021) and use projections from the Coupled Model Comparison Project (CMIP) repository. The third proxy uses one-month weather futures returns as traded in the CME. With these monthly observations, we then repeat the procedure previously implemented to estimate betas, but in this case firms' exposure is with respect to temperature shocks. In turn, we sort stocks based on their previous months betas, buying stocks with most negative betas while selling stocks with most positive betas. In the Appendix, Table A.6 reports the average alphas from the long-short strategy, which in all cases render insignificant. The findings in Table A.6 are consistent with Addoum, Ng and Ortiz-Bobea (2023), who document that stock prices are generally unresponsive to temperature shocks. Combined with our previous result of Table 6, this suggest that it is the uncertainty about future temperature oscillations and not the expectations about future temperature what seems to have an impact on firms' fundamentals and ultimately equity values.

Overall, we find significant results for the return effect of $\beta^{\Delta WIVOL}$. The negative link between firms' beta and their future returns at the portfolio and individual level is consistent with an investors' intertemporal hedging motive. On the one hand, stocks with negative betas correlate negatively with increases in expected weather volatility; hence, investors demand extra compensation in the form of higher expected return to hold these stocks. On the other hand, stocks with positive betas correlate positively with increases in expected weather volatility. Since stocks with positive beta would be viewed as relatively safer assets at times of increased volatility, investors are willing to pay higher prices and accept lower expected returns.

5.4 Firm Characteristics and Return Predictability

How can weather volatility shocks, local and idiosyncratic in nature, affect firms' expected returns? In the theoretical motivation, we build on Merton's (1987) framework to demonstrate that local weather volatility can influence asset prices through the shadow cost associated with the incomplete diffusion of information among investors. Traditional asset pricing models often assume that all publicly available information is instantaneously disseminated and acted upon by investors. However, Merton (1987) highlights that acquiring and processing information incurs costs, leading investors to deviate from holding the market portfolio as predicted by the capital asset pricing model.[18] In this section, we explore this hypothesis by investigating the impact of local weather volatility shocks. More specifically, we hypothesize

[18]In addition to the information friction, several other factors, such as market segmentation, institutional restrictions, taxes, and transaction costs, can play an important role as well.

that, holding constant the dispersion in the sensitivity to local weather volatility shocks, the performance of the long-short strategy using a subset of firms with higher informational friction costs is stronger.

To test this hypothesis, we begin by examining whether exposure to local weather uncertainty shocks influences firm policies, leading to differences in firm characteristics associated with stock return predictions. Specifically, we compare the average constituent firm characteristics across WIVOL quintiles. These characteristics include cash flow levels, profitability, leverage, investment, book-to-market ratios, and Altman's z-score. The results presented in Panel A of Table A.7 reveal no consistent monotonic relationship between WIVOL exposure and these characteristics, except for investment, which exhibits a positive association with $\beta^{\Delta WIVOL}$. These findings suggest that the observed cross-sectional predictive power of WIVOL exposure is unlikely to be driven by these characteristics. Additionally, Panel B of Table A.7 reports the average WIVOL exposure across six broad sectors, revealing significant dispersion in $\beta^{\Delta WIVOL}$ within each sector. This suggests that portfolios with low and high $\beta^{\Delta WIVOL}$ are not dominated by a single sector, reinforcing that our main empirical findings are unlikely driven by industry-specific characteristics.

Next, we conduct independent double sorts based on firms' WIVOL beta and various proxies that reflect the degree of information friction associated with the stock. We then assess the performance of the long-short (Low minus High) WIVOL beta strategy within each group. For these proxies, we consider the degree of institutional investor holdings as per Merton (1987), the extent of hedge fund ownership, the number of institutional owners situated in the same country (the United States) and city (New York), as well as the ownership concentration measured by the Herfindahl index. All five variables are orthogonalized with respect to the firm size.

In columns 1 to 4 of Table 8 show that abnormal returns of the long-short WIVOL beta sorted portfolios are statistically significant only among stocks with the low level of institutional and hedge funds holdings. However, in columns 5 and 6, where ownership concentration is measured using the Herfindahl index, we observe the opposite pattern, as neglected stocks tend to have a high level of concentration.

[Insert Table 8 Here]

Information asymmetry can induce a local bias in ownership within financial markets, as proximate investors often possess superior access to firm-specific information, increasing their confidence and perceived reduction in investment risk. In contrast, distant investors encounter higher costs and difficulties in acquiring equivalent information, leading to their aversion to such investments. This informational disparity ultimately results in a concentration of ownership among geographically proximate investors. Building on this concept, we investigate the heterogeneity in local ownership levels, hypothesizing that higher local ownership reflects greater information friction and consequently diminished risk-sharing abilities among investors. In columns 7 to 10 of Table 8, we quantify the number of investors located in the same country (United States) as per Coval and Moskowitz (1999) and those in the same city (New York) as per Baik, Kang, and Kim (2010) and Bernile, Kumar, and Sulaeman (2015), respectively.[19] Our findings reveal that abnormal returns of long-short WIVOL beta-sorted portfolios are statistically significant only within high local ownership, after controlling for size. In summary, this lends support to the hypothesis that information friction and investor recognition are an important determinants of the predictable patterns in WIVOL beta's impact on local stock returns.

Second, we examine whether WIVOL predictability is associated with sensitivity to local discount rate shocks. When local weather conditions become more volatile, local investors are likely to become more risk-averse, potentially diminishing their capacity for risk-sharing. This can result in a decline in current stock prices and an increase in average future returns (see, for example, Korniotis and Kumar (2013)). In the subsequent tests, we assess which

[19] The information about firm level institutional holdings is sourced from the FactSet Ownership database.

groups of firms are more susceptible to these local discount rate shocks. To address this, we utilize three proxies for local discount rate sensitivities: local operational presence, measured by the number of employees in New York[20]; reliance on labor productivity growth as a source of income, measured by the growth rate of sales per employee; and equity durations, as defined by Dechow, Sloan, and Soliman (2004). We expect that abnormal returns would be more pronounced for stocks with a substantial operational presence in the local economy, firms that have seen notable increases in labor productivity growth (thus generating significant returns to human capital, which is predominantly local in nature), and firms with cash flows that are concentrated in the distant future. Table 9 demonstrates that WIVOL beta's impact on local stock returns is considerably stronger among those firms that are more exposed to local discount rate shocks, as indicated by a high share of local employees, their productivity growth, and high equity duration.

[Insert Table 9 Here]

Third, we evaluate the performance of the long-short based on proxies of firm profitability. These proxies include operating profit (OperProf), defined as revenue minus cost minus administrative expenses minus interest expenses, scaled by book value of equity, and return on assets, calculated as net income over book value of assets. The analysis shows no economically significant differences in abnormal returns between the two groups of long-short WIVOL beta-sorted portfolios, with statistically significant abnormal returns only observed within the more profitable groups. This empirical observation indicates that our findings are not mainly driven by risk premium embedded in common variations in stock returns among constrained firms due to shocks to the macroeconomic environment, credit conditions, intermediary capital constraints, or monetary policy (Lamont, Polk and Saa-Requejo (2001), He, Kelly, and Manela (2017)). To the extent that more profitability face reduced financial constraints to adapt, our results are not driven by financial frictions that prevent the

[20]The establishment level employee statistics are obtained from National Establishment Time-Series (NETS) Database

firm from implementing risk mitigation strategies. Additionally, we confirm that our results are not primarily driven by financial frictions associated with firm size by demonstrating that average returns of the long-short portfolio are more pronounced among firms with high equity market capitalization (size).

Taken together, the findings in this section suggest that local weather volatility shocks, despite being idiosyncratic, can influence a firms' expected returns because of information frictions among investors. Our findings reveal that abnormal returns are statistically significant among stocks with low institutional holdings and high local ownership, underscoring the importance of information asymmetry in asset pricing. Furthermore, we demonstrate that firms with substantial local operational presence and productivity growth are more sensitive to local discount rate shocks, resulting in stronger returns. Lastly, we find that abnormal returns are more pronounced in profitable firms, indicating that our results are driven by the costs associated with information acquisition and investor recognition, rather than financial frictions.

5.5 Firms Exposure to Foreign Weather Risk

Section 4 documents that WIVOL moves along with local physical and regulatory weather risks, while Section 5.3 finds that local firms exhibit significant exposure to innovations in WIVOL. We therefore expect for local firms to exhibit stronger WIVOL exposure than non-local firms, which are based in a different geographic location.

We test this local exposure hypothesis next. We implement a similar exercise but this time use option prices based on the temperatures recorded in the metro area of Dallas Fort-Worth (DFW) in the state of Texas.[21] As in the case of WIVOL for the city of New York, we collect CME data on prices for options, futures, strikes, expiration dates and implied volatilities. To generate the time-series for the weather option implied volatility WIVOL,

[21] Specifically, the contract's payoff is with respect to the temperature (in degree-days) measured at the Dallas Fort-Worth International (DFW) airport station (WBAN 03927).

we use closest to one month maturity contracts that are at-the-money. We then compute the exposure of local firms to WIVOL DFW. We restrict the set to firms headquartered only in the cities of Dallas and Fort-Worth, based on a firm's city, state and zip code attributes. For the sample period of January 2005 to July 2021 this generates a total of 441 firms, with an average (median) of 101 (105) firms per month. We then estimate the exposure of DFW firms to WIVOL DFW and test its predictive power. Following the argument of Section 5.3, the long-short strategy entails buying stocks with most negative betas while simultaneously selling stocks with most positive betas. We find that the long-short strategy generates positive and statistically significant returns, even after controlling for well established risk factors. We also test the significance of the beta return effect at the individual firm level with Fama-MacBeth predictive regressions and find a negative and statistically significant coefficient, indicating that, on average, firms with lower exposure to WIVOL exhibit higher future returns. These results, reported in Table A.8 and Table A.9 respectively, support the hypothesis that the exposure of local firms to innovations in local weather risk is significant and helps predict firms' future performance.

Several studies find that measures that track global weather events have a significant impact on geographically dispersed entities (see, for instance, Engle, Giglio, Kelly, Lee and Stroebel (2020) and Huynh and Xia (2021)). The local nature of WIVOL (based on the temperature of a geography specific weather station) provides an interesting tool to test the extent to which firms based in one area are impacted by innovations in weather volatility of a different area. Therefore, we next test whether market expectations of weather volatility for New York (Dallas) contain significant information about the future performance of firms based in Dallas (New York). Specifically, we link WIVOL measured for the city of New York to firms based in the Dallas Forth-Worth area. This produces betas for DFW firms with respect to innovations in the weather volatility of New York, which we use to predict future stock returns of firms in DFW. Likewise, we estimate betas for New York based firms using innovations in the weather volatility of the Dallas Fort-Worth area. We use these betas to predict the future stock returns of firms based in New York. If we find significant exposure, then the local risk hypothesis does not hold, as both measures of risk become indistinguishable.

We test this argument by sorting quintile portfolios, buying stocks with most negative exposure (quintile 1) and selling stocks with most positive exposure (quintile 5). Interestingly, we find insignificant return predictability in both cases. Betas constructed using New York weather volatility do not predict the future return of firms based in the Dallas Fort-Worth metro area. Likewise, betas estimated using DFW weather volatility do not predict the future return of New York based firms. We report these results in Table 10. These findings support the argument that, while firms can be subject to global climate risks, local firms are more exposed to local weather risk than non-local firms. Tuzel and Zhang (2017) document that firms location affect firms risk through local factor prices such as real estate and labor, while Kruttli, Roth Tran and Watugala (2023) find that firms located in hurricane prone area exhibit higher volatility of returns. Our findings are of first order, as local firms with more negative exposure to local weather risk exhibit higher future returns.

[Insert Table 10 Here]

6 Conclusion

We investigate on the relevance of weather volatility for firms' performance. To the best of our knowledge, this is the first study using investors' expectations about weather risks, which can only be extracted using weather option prices. We denote this new, forward-looking variable WIVOL, the weather option implied volatility. We find that WIVOL captures markets expectations about future shocks to weather risk, increasing with the likelihood of physical events such as hurricanes and with discussions about regulations to transition to an environmentally friendlier economy.

We find that innovations to WIVOL significantly increase operating costs and uncertainties associated with those fundamentals. We document that firm-level exposure to idiosyncratic weather risk shocks impact expected returns, a result we theoretically motivate with a dynamic model where firms' cash-flows change with weather volatility when investors are unaware of the parameters governing the return process of the security. Firms with more negative exposure to WIVOL innovations are valued at a discount because expectations of larger oscillations in temperatures lead to a higher risk of unexpected costs for the company. Investors, therefore, demand a weather risk compensation to hold these stocks. We find that weather volatility risks are priced, a long-short strategy that buys stocks with more negative exposure and sells stocks with more positive exposure generates significant returns after controlling for different risk factors. Moreover, unlike strategies based on extreme events that are likely seasonal, the WIVOL strategy can be implemented year-round. We also confirm that firms are significantly exposed to the volatility of weather of the area in which they operate only, as innovations to weather volatility of a different area do not predict their future returns.

Appendix: Expected Returns and Weather Risk: A Dynamic Model

We first describe the stochastic process for firm k cash-flows, followed by the constrained optimization problem for investor j. We then aggregate across all investors to derive the market equilibrium return for the firm, which depends on its idiosyncratic weather risk. The model follows Merton (1987). Kruttli, Roth Tran and Watugala (2023) extend Merton (1987) with an additional weather rare-event type of risk. Unlike rare-events, weather volatility risk is a continuous random variable that does not rely on the preocurrence of a rare-event with potential systematic reach.

The end of period cash flow for firm k is

$$\widetilde{C}_k = I_k \left[a_k + b_k \widetilde{Y} + s_k \widetilde{\epsilon}_k + u_k \widetilde{\upsilon}_k \right] \tag{A.1}$$

where a tilde denotes a random variable, with $E(\widetilde{x}) = 0$ and $E(\widetilde{x}^2) = 1$ for $x = (\widetilde{Y}, \widetilde{\epsilon}_k, \widetilde{\upsilon}_k)$. Cash-flows are impacted by independent oscillations in the market factor $\widetilde{Y}$, the idiosyncratic random variable $\widetilde{\epsilon}_k$ and the firm-specific weather risk variable $\widetilde{\upsilon}_k$.

The end of period return on firm k is

$$\widetilde{R}_k = \mu_k + \eta_k \widetilde{Y} + \varphi_k \widetilde{\epsilon}_k + \sigma_k \widetilde{\upsilon}_k \tag{A.2}$$

with firm value V_k and $\widetilde{R}_k \equiv \widetilde{C}_k / V_k$, $\mu_k \equiv a_k I_k / V_k$, $\eta_k \equiv b_k I_k / V_k$, $\varphi_k \equiv s_k I_k / V_k$, $\sigma_k \equiv u_k I_k / V_k$.

The portfolio optimization problem for investor j involves the selection of securities. The weight $w_{k,j}$ is the fraction of wealth investor j allocates in security k. There are n firms in the economy and $n+2$ securities. The two additional securities are a forward contract with cash-settlement on the market factor and return $\widetilde{R}_{n+1} = \mu_{n+1} + \widetilde{Y}$, and the risk free security with return R_f.

The portfolio return and risk exposures for investor j are

$$\widetilde{R}_j = \mu_j + \eta_j \widetilde{Y} + \varphi_j \widetilde{\epsilon}_j + \sigma_j \widetilde{\upsilon}_j \tag{A.3}$$

$$\eta_j = \sum_{k=1}^{n} w_{k,j} \eta_k + w_{n+1,j} \tag{A.4}$$

$$\varphi_j^2 = \sum_{k=1}^{n} w_{k,j}^2 \varphi_k^2 \tag{A.5}$$

$$\sigma_j^2 = \sum_{k=1}^{n} w_{k,j}^2 \sigma_k^2 \tag{A.6}$$

The expected return and variance of the portfolio for investor j are

$$E(\widetilde{R}_j) = R_f + \eta_j(\mu_{n+1} - R_f) - \sum_{k=1}^{n} w_{k,j}\Delta_k \tag{A.7}$$

$$Var(\widetilde{R}_j) = \eta_j^2 + \sum_{k=1}^{n} w_{k,j}(\varphi_k^2 + \sigma_k^2) \tag{A.8}$$

with $\Delta_k \equiv R_k - R_f - \eta_k(\mu_{n+1} - R_f)$.[22] The optimization problem for investor j is

$$\underset{\eta_j, w_j}{Max} \left[E(\widetilde{R}_j) - \frac{\delta_j}{2} Var(\widetilde{R}_j) + \sum_{k=1}^{n} w_{k,j}\lambda_{k,j} \right] \tag{A.9}$$

The last term in equation (A.9) introduces a friction to an otherwise standard mean-variance optimization for a risk-averse investor. The additional constraint relates to the investor's knowledge about firm $k's$ parameters $(\mu_k, \eta_k, \varphi_k^2, \sigma_k^2)$ in equation (A.2). If investor j knows about firm k then the Khun-Tucker multiplier $\lambda_{k,j} = 0$. Conversely, if investor j does not know about firm k, $w_{k,j} = 0$. Known firms by investor j belong to the set S_k, while unknown firms belong to the set S_k^c.

The first order conditions for η_j and w_j are

$$0 = \mu_{n+1} - R_f - \delta_j \eta_j \tag{A.10}$$

$$0 = \Delta_k - \delta_j w_{k,j}(\varphi_k^2 + \sigma_k^2) - \lambda_{k,j} \tag{A.11}$$

[22] We use the result that $w_{n+2,j} = 1 - \sum_{k=1}^{n+1} w_{k,j}$

The common factor exposure and portfolio weights for each security are

$$\begin{aligned}
\eta_j &= \frac{\mu_{n+1} - R_f}{\delta_j} && \text{(A.12)}\\
w_{k,j} &= \frac{\Delta_k}{\delta_j(\varphi_k^2 + \sigma_k^2)}, \quad \text{for } k \in S_k && \text{(A.13)}\\
w_{k,j} &= 0, \ \text{ for } k \in S_k^c && \text{(A.14)}\\
w_{n+1,j} &= \eta_j - \sum_{k=1}^{n} w_{k,j}\eta_k && \text{(A.15)}\\
w_{n+2,j} &= 1 - \eta_j - \sum_{k=1}^{n} w_{k,j}(\eta_k - 1) && \text{(A.16)}
\end{aligned}$$

We next aggregate across all investors to determine the optimal demand for each security. There are N investors in the economy with identical preferences and initial wealth, $\delta_j = \delta$ and $W_j = W$, with the equilibrium total market wealth $M \equiv NW$. Therefore, each investor exhibits identical market factor exposure. From equation (A.12)

$$\mu_{n+1} = R_f - \delta\eta \tag{A.17}$$

The aggregate demand for security k is D_k , determined by the set of investors N_k that know about the security. Using the weights in equation (A.13)

$$D_k = N_k W \frac{\Delta_k}{\delta(\varphi_k^2 + \sigma_k^2)} \tag{A.18}$$

In addition, the aggregate demand for the market factor and risk-free security are zero in equilibrium.[23] Denote the proportion of investors that know about firm k as $q_k \equiv \frac{N_k}{N}$. The proportion of firm k relative to the market is $x_k \equiv \frac{V_k}{M}$ and in equilibrium $D_k = V_k$. Therefore, using equation (A.18)

$$x_k = \frac{q_k \Delta_k}{\delta(\varphi_k^2 + \sigma_k^2)} \tag{A.19}$$

Using equations (A.12), (A.17) and (A.19), the equilibrium expected excess return for security k is

$$E(\widetilde{R}_k) - R_f = \eta_k \eta \delta + \frac{\delta x_k(\varphi_k^2 + \sigma_k^2)}{q_k} \tag{A.20}$$

The elasticity of the expected excess return of security k with respect to its firm-specific

[23] $D_{n+1} = NW\eta - \sum_{k=1}^{n} D_k \eta_k$ and $D_{n+2} = NW\eta - \sum_{k=1}^{n+1} D_k$.

weather risk

$$\frac{d\log(E(\widetilde{R}_k) - R_f)}{d\log(\sigma_k^2)} = \frac{x_k(\sigma_k^2)}{q_k\eta_k\eta + x_k(\varphi_k^2 + \sigma_k^2)} \tag{A.21}$$

which indicates that idiosyncratic weather risk shocks increase expected returns.

To investigate the impact of weather risk on firm value V_k, we use equation (A.2) together with equation (A.20)

$$V_k = \frac{I_k}{R_f}\left[a_k - \delta\eta b_k - \frac{\delta(s_k^2 + u_k^2)I_k}{q_k M}\right] \tag{A.22}$$

The value of firm k is lower compared to the case of no idiosyncratic risk in place V_k^*

$$V_k = V_k^* - (s_k^2 + u_k^2)\frac{(1-q_k)\,\delta}{q_k R_f M} \tag{A.23}$$

Therefore, the impact on firm value V_k is analogous to cash-flows being discounted at a higher rate in the presence of idiosyncratic weather risk

$$V_k = \frac{V_k^*}{1 + \left[(\varphi_k^2 + \sigma_k^2)\frac{(1-q_k)x_k\delta}{q_k R_f}\right]} \tag{A.24}$$

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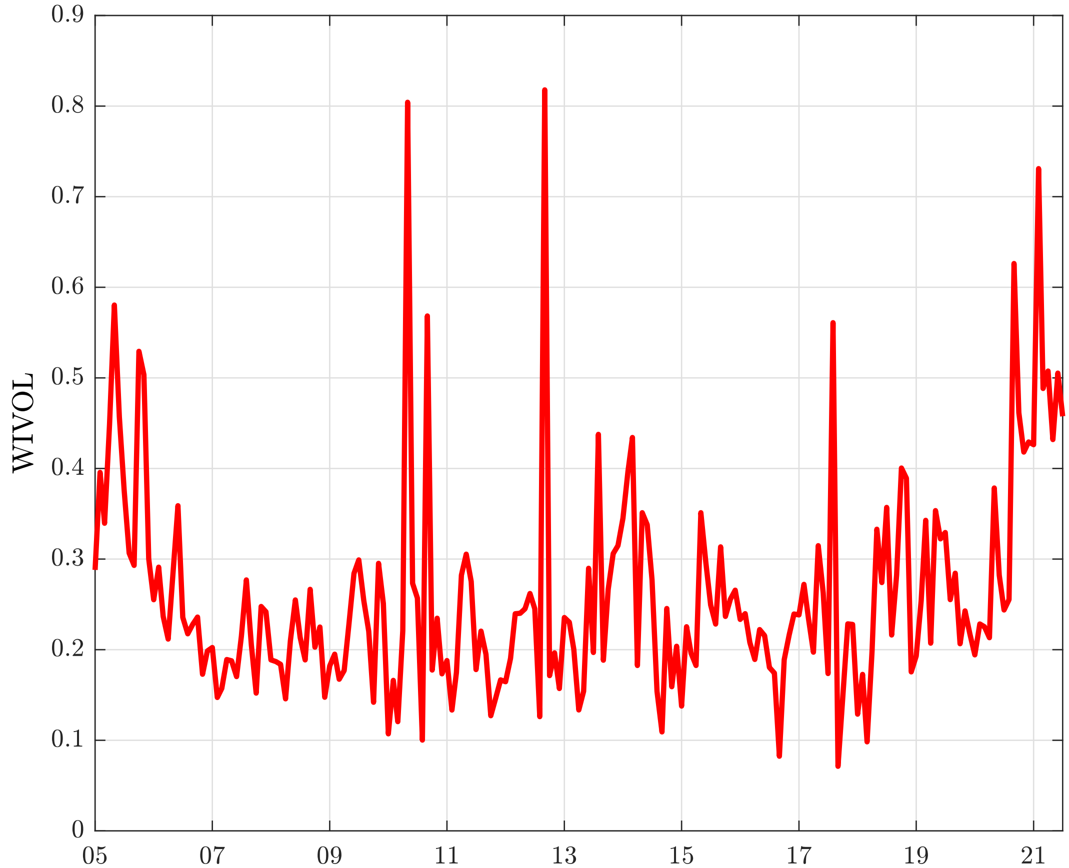

Figure 1: Weather Option Implied Volatility

We plot the time-series for WIVOL, the option implied volatility using weather options on futures contracts based on the temperature registered at the LaGuardia Airport in the city of New York. The time-series is constructed using one month to maturity contracts for at-the-money options. We report monthly average values. The sample period is from January 2005 to July 2021.

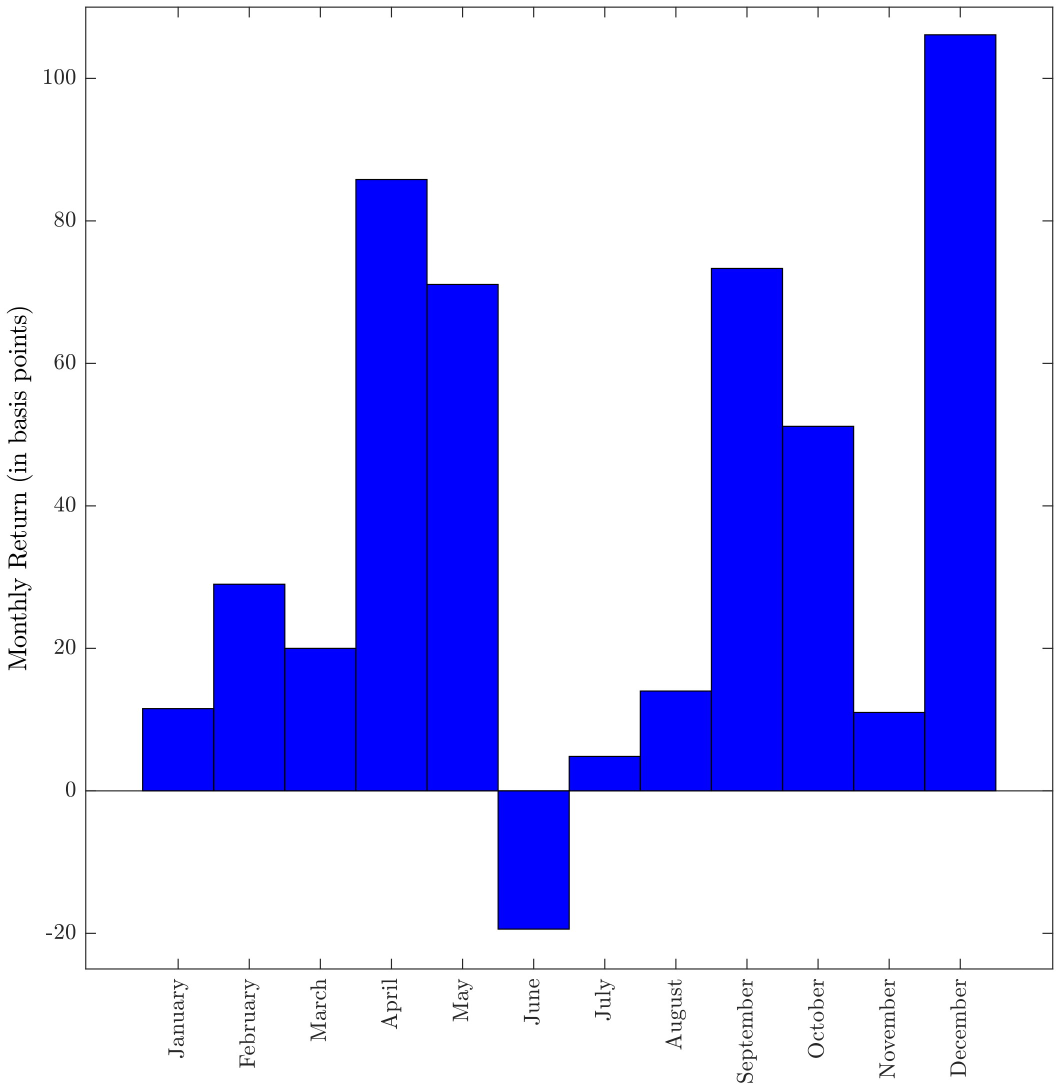

Figure 2: Average Long-Short Strategy Return By Month

We plot average monthly returns for the long-short $\beta^{\Delta WIVOL}$ strategy. The strategy buys stocks with most negative $\beta^{\Delta WIVOL}$ and sells stocks with most positive $\beta^{\Delta WIVOL}$. The bar represents the average return (in basis points) in each month and for the sample period January 2008 to July 2021.

Table 1: Summary Statistics

We report the summary statics of variables used in the paper. The variables include: the changes in the weather option implied volatility (ΔWIVOL), the logarithm of the firm's market capitalization (*Size*), the book-to-market ratio (*Book-to-Market*), the gross protability (*Profitability*) as in Novy-Marx (2013), the logarithm of the number of months since a listing date (*Age*), the book leverage (*Levearge*) defined as short- and long-term debt, scaled by the total debts and common equity, the aveverage number of shares tradedF over the previous three months scaled by shares outstanding (*Share Volume*), the logarithm of the price (*Price*), the cumulated past performance in the previous year by skipping the most recent month (*Momentum*), and the earnings to price ratio (*Earnings-to-Price*), the logarithm of the cost of goods sold ($ln(COGS)$), the selling, general and administrative expense ($ln(XSGA)$), the total operating expense ($ln(XOPR)$), the inventory costs ($ln(INVT)$), the revenue ($ln(SALES)$), the monthly change in the mean earnings estimate for the next fiscal quarter, scaled by lagged stock price (Revision), the absolute values of the quarterly changes in the firm's revenue scaled by the last quarter's total asset (|ΔSALES|), the cost of goods sold (|ΔCOGS|), the selling, general, and administrative expense (|ΔXSGA|), and the total operating expense (|ΔXOPR|), the absolute values of the standardized unexpected earnings (|SUE|), the first difference of call option implied volatility with 30 days of maturity and delta of 0.5 ($\Delta ImpVolCall$), put option implied volatility with delta of -0.5 ($\Delta ImpVolPut$), and the implied volatility of put option with moneyness closest to but above 1 minus that of call option with moneyness closest to but below 1 ($SKEW$).

Variable Name	Mean	STDEV	p10	p25	p50	p75	p90
ΔWIVOL	0.005	0.157	-0.133	-0.064	0.008	0.090	0.157
Size	13.827	2.445	10.609	12.017	13.852	15.620	17.057
Book-to-Market	0.599	0.542	0.117	0.246	0.477	0.784	1.192
Profitability	0.066	0.087	0.000	0.013	0.054	0.108	0.167
Age	4.910	1.001	3.434	4.205	5.056	5.689	6.176
Leverage	0.426	0.393	0.000	0.091	0.387	0.635	0.863
Share Volue	1.941	2.087	0.263	0.706	1.368	2.403	4.143
Price	2.742	1.442	0.732	1.847	2.970	3.758	4.343
Momentum	-0.042	0.554	-0.678	-0.246	0.037	0.250	0.485
Earnings-to-Price	-2.970	0.806	-3.926	-3.371	-2.893	-2.501	-2.143
ln(SALES)	5.299	2.595	2.035	3.696	5.496	7.190	8.318
ln(COGS)	4.706	2.437	1.472	3.020	4.893	6.415	7.840
ln(XSGA)	3.863	2.252	0.917	1.984	3.964	5.649	6.609
ln(XOPR)	4.927	2.440	1.679	3.107	5.043	6.792	7.983
ln(INVT)	4.835	3.068	0.644	2.991	5.115	6.738	7.802
|ΔSALES|	0.060	1.424	0.001	0.003	0.013	0.040	0.093
|ΔCOGS|	0.049	1.344	0.000	0.002	0.008	0.025	0.068
|ΔXSGA|	0.023	0.129	0.000	0.001	0.005	0.016	0.042
|ΔXOPR|	0.062	1.362	0.001	0.003	0.012	0.038	0.101
$\mid SUE \mid$	2.354	2.668	0.200	0.667	1.500	3.000	5.208
ΔImpVolCall	0.011	0.198	-0.106	-0.032	0.012	0.055	0.139
ΔImpVolPut	0.014	0.193	-0.105	-0.031	0.011	0.056	0.132
SKEW	0.067	0.072	0.017	0.033	0.051	0.078	0.131
Revision	0.003	0.228	-0.044	-0.008	0.002	0.011	0.035

Table 2: WIVOL and Financial, Macro, and Real Indicators

We report results from time-series regressions in which the change in the weather option implied volatility, $\Delta WIVOL$, is regressed on variables noted in the column ID. *CC* is the climate change news index from Engle, Giglio, Kelly, Lee and Stroebel (2020), *HOUST* is the total new privately owned housing starts, *FEDFUNDS* is the change in effective Federal Fund Rate, *TS* denotes the change in term spread (10 year minus 3 month rates), *Inter_cap_ratio* and *Inter_risk_factor* are intermediary capital ratio and intermediary risk factor of He, Kelly, and Manela (2017), respectively, *UNRATE* denotes the change in the civilian unemployment rate, *INDPRO* is the growth rate of the industrial production index, *SP_PE_ratio* and *SP500* represent the price-earnings ratio and the return of the S&P 500 index, respectively. *EPU* denotes the change in the political uncertainty index of Baker, Bloom, and Davis (2016), *Fuh*, *Muh*, and *Ruh* are the change in financial, macro, and real uncertainty of Jurado, Ludvigson, and Ng (2015), respectively, and *VIX* is the change in the implied volatility of the S&P 500 index. We report the Newey-West corrected t-statistics.

ID	**Coefficient**	**t-stat**	**Description**	**Group**	**R-Square**
CC	1.88	0.58	Climate Change News Index	Climate News	0.00
HOUST	0.00	-0.08	Housing Starts growth	Housing	0.00
FEDFUNDS	0.12	0.81	Fed Funds Rate change	Interest Rates	0.00
TS	0.08	0.31	Term Spread change	Interest Rates	0.00
Inter_cap_ratio	-0.18	-1.00	Intermediary Capital Ratio change	Intermediary Capital	0.00
Inte_risk_factor	-0.01	-0.82	Intermediary Factor return	Intermediary Capital	0.00
UNRATE	-0.01	-0.34	Unemployment change	Labor Market	0.00
INDPRO	-0.04	-0.89	IP growth	Output and Income	0.00
SP_PE_ratio	-0.01	-0.27	PE ratio change	Stock Market	0.00
SP500	-0.01	-0.77	Stock Market Return	Stock Market	0.00
EPU	0.29	1.12	Policy Uncertainty change	Uncertainty - Economic Policy	0.01
Fuh	0.63	0.46	Financial Uncertainty change	Uncertainty - Financial	0.00
Muh	0.83	0.45	Macro Uncertainty change	Uncertainty - Macro	0.00
Ruh	1.69	0.84	Real Uncertainty change	Uncertainty - Real	0.00
VIX	0.02	1.10	VIX change	Uncertainty - Stock Market	0.01

Table 3: WIVOL and Firm Fundamentals

We report the effect of the weather implied volatility on the firms' fundamental levels using panel regressions. The dependent variables are the logarithm of the cost of goods sold (Column 1), the selling, general and administrative expense (Column 2), the total operating expense (Column 3), the inventory costs (Column 4), the revenue (Column 5), the monthly change in the mean earnings estimate for the next fiscal quarter, scaled by lagged stock price (Column 6). The main explanatory variable is ΔWIVOL, the changes in the weather option implied volatility. The control variable includes the logarithm of the firm's market capitalization (*Size*), the book-to-market ratio (*Book-to-Market*), the gross protability (*Profitability*) as in Novy-Marx (2013), the logarithm of the number of months since a listing date (*Age*), the book leverage (*Levearge*) defined as short- and long-term debt, scaled by the total debts and common equity, the aveverage number of shares traded over the previous three months scaled by shares outstanding (*Share Volume*), the logarithm of the price (*Price*), the cumulated past performance in the previous year by skipping the most recent month (*Momentum*), and the earnings to price ratio (*Earnings-to-Price*). We report in parentheses the t-statistics controlling for firm and year fixed effects and clustering standard errors at the firm level. All explanatory variables are one-quarter lagged.

Dependent Variable	ln(COGS)	ln(XSGA)	ln(XOPR)	ln(INVT)	ln(SALES)	Revision
	(1)	(2)	(3)	(4)	(5)	(6)
Intercept	-0.793	-0.628	-0.523	-0.241	-1.170	2.371
	(-2.65)	(-1.93)	(-2.11)	(-0.70)	(-2.92)	(1.11)
ΔWIVOL	0.053	0.069	0.063	0.135	0.018	-0.381
	(2.04)	(2.97)	(2.37)	(2.84)	(0.70)	(-2.31)
Size	0.092	0.086	0.076	0.067	0.170	-0.348
	(3.45)	(3.08)	(3.60)	(2.29)	(3.59)	(-1.66)
Book-to-Market	0.107	0.165	0.119	0.061	0.138	0.298
	(2.93)	(3.49)	(3.88)	(1.33)	(3.05)	(0.66)
Profitability	2.083	1.233	1.782	-1.164	3.628	5.501
	(4.00)	(4.49)	(4.14)	(-3.96)	(4.71)	(4.90)
Age	0.066	0.031	0.027	0.031	0.022	-0.211
	(1.90)	(1.11)	(1.15)	(0.91)	(0.69)	(-1.31)
Leverage	0.092	0.128	0.079	0.075	0.183	0.276
	(1.34)	(1.85)	(1.41)	(1.13)	(1.84)	(1.14)
Share Volume	-0.003	-0.000	-0.000	0.011	-0.007	-0.145
	(-0.54)	(-0.02)	(-0.09)	(2.15)	(-1.17)	(-2.49)
Price	-0.008	0.020	0.001	0.020	-0.039	0.858
	(-0.32)	(0.65)	(0.07)	(0.89)	(-1.31)	(2.27)
Momentum	-0.036	-0.019	-0.026	-0.014	-0.015	0.702
	(-2.33)	(-1.44)	(-1.94)	(-0.71)	(-0.99)	(3.40)
Earnings-to-Price	-0.007	-0.001	-0.006	-0.007	-0.005	-0.131
	(-0.75)	(-0.15)	(-0.87)	(-1.00)	(-0.53)	(-1.65)
Lagged Dependent	0.798	0.769	0.835	0.831	0.723	0.821
	(13.87)	(20.01)	(18.94)	(30.49)	(7.50)	(37.85)
R^2_{Adj}	0.982	0.988	0.986	0.988	0.980	0.709
N	4935	3468	5043	3272	4968	13015
Firm Fixed	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed	Yes	Yes	Yes	Yes	Yes	Yes
Frequency	Quarterly	Quarterly	Quarterly	Quarterly	Quarterly	Monthly

Table 4: WIVOL and Fundamental Uncertainty

We report the effect of the weather implied volatility on the firms' fundamental uncertainties using panel regressions. The dependent variables are the absolute values of the quarterly changes in the firm's revenue (Column 1), the cost of goods sold (Column 2), the selling, general, and administrative expense (Column 3), and the total operating expense (Column 4). All dependent variables are scaled by the last quarter's total asset. The main explanatory variable is ΔWIVOL, the changes in the weather option implied volatility. The control variable includes the logarithm of the firm's market capitalization (*Size*), the book-to-market ratio (*Book-to-Market*), the gross protability (*Profitability*) as in Novy-Marx (2013), the logarithm of the number of months since a listing date (*Age*), the book leverage (*Levearge*) defined as short- and long-term debt, scaled by the total debts and common equity, the avev-erage number of shares traded over the previous three months scaled by shares outstanding (*Share Volume*), the logarithm of the price (*Price*), the cumulated past performance in the previous year by skipping the most recent month (*Momentum*), and the earnings to price ratio (*Earnings-to-Price*). We report in parentheses the t-statistics controlling for firm and year fixed effects and clustering standard errors at the firm level. All explanatory variables are one-quarter lagged.

Dependent Variable	|ΔSALES|	|ΔCOGS|	|ΔXSGA|	|ΔXOPR|
	(1)	(2)	(3)	(4)
Intercept	0.080	0.026	0.055	0.049
	(0.72)	(0.28)	(2.38)	(0.50)
$\Delta WIVOL$	0.017	0.015	0.002	0.016
	(2.22)	(2.12)	(1.67)	(2.21)
Size	-0.003	-0.001	-0.002	-0.001
	(-0.32)	(-0.08)	(-1.42)	(-0.15)
Book-to-Market	0.005	0.008	-0.006	0.006
	(0.56)	(1.11)	(-2.84)	(0.74)
Profitability	0.013	0.051	-0.035	0.012
	(0.19)	(1.14)	(-2.03)	(0.22)
Age	-0.005	-0.003	-0.003	-0.003
	(-1.28)	(-1.27)	(-1.48)	(-1.30)
Leverage	-0.001	-0.004	0.009	-0.002
	(-0.08)	(-0.33)	(2.53)	(-0.19)
Share Volume	0.001	0.001	-0.000	0.001
	(1.11)	(1.40)	(-0.16)	(1.06)
Price	0.002	0.000	-0.002	-0.000
	(0.16)	(0.02)	(-1.75)	(-0.03)
Momentum	0.002	0.005	-0.001	0.003
	(0.24)	(0.50)	(-1.70)	(0.37)
Earnings-to-Price	0.002	0.000	0.000	0.001
	(1.10)	(0.34)	(1.04)	(0.82)
Lagged Dependent	0.652	0.668	0.370	0.663
	(21.10)	(35.78)	(12.89)	(29.53)
R^2_{Adj}	0.549	0.571	0.529	0.564
N	4353	4355	2969	4355
Firm Fixed	Yes	Yes	Yes	Yes
Year Fixed	Yes	Yes	Yes	Yes
Frequency	Quarterly	Quarterly	Quarterly	Quarterly

Table 5: WIVOL and Fundamental Uncertainty using Alternative Measures

We report the effect of the weather implied volatility on the firms' fundamental uncertainties using panel regressions. The dependent variables are the firms' climate change risk exposure, measured by managers' discussion on climate change risk during earnings calls (Column 1), the absolute values of the standardized unexpected earnings, calculated as the actual earnings minus the mean analyst expected earnings, scaled by the standard deviation of the analyst forecasts (Column 2), the first difference of call option implied volatility with 30 days of maturity and delta of 0.5 (Column 3), the first difference of put option implied volatility with 30 days of maturity and delta of -0.5 (Column 4), and the implied volatility of put option with moneyness closest to but above 1 minus that of call option with moneyness closest to but below 1 (Column 5). The main explanatory variable is ΔWIVOL, the changes in the weather option implied volatility. All regressions include control variables described in Table 3 and 4 of the paper. We report in parentheses the t-statistics controlling for firm and year fixed effects and clustering standard errors at the firm level. All explanatory variables are one-quarter lagged.

Dependent Variable	CCRisk	$\mid SUE \mid$	ΔImpVolCall	ΔImpVolPut	SKEW
	(1)	(2)	(3)	(4)	(5)
Intercept	-1.798	4.795	-0.032	-0.036	0.085
	(-1.31)	(1.60)	(-0.74)	(-0.83)	(1.83)
ΔWIVOL	0.234	0.824	0.032	0.033	0.007
	(1.98)	(2.52)	(3.85)	(3.88)	(1.75)
Size	0.066	-0.196	0.001	0.000	-0.001
	(0.76)	(-0.76)	(0.26)	(0.04)	(-0.34)
Book-to-Market	0.126	-0.310	-0.006	-0.004	-0.005
	(0.75)	(-1.02)	(-1.09)	(-0.62)	(-1.10)
Profitability	0.545	0.754	-0.023	-0.028	-0.025
	(0.74)	(0.45)	(-0.47)	(-0.44)	(-0.92)
Age	-0.010	0.143	0.005	0.005	0.000
	(-0.09)	(0.69)	(1.74)	(1.67)	(0.01)
Leverage	0.242	-0.221	0.004	-0.003	-0.005
	(0.70)	(-0.62)	(0.68)	(-0.55)	(-0.77)
Share Volume	-0.001	-0.018	-0.003	-0.002	0.000
	(-0.07)	(-0.39)	(-2.71)	(-1.61)	(0.18)
Price	0.225	-0.075	-0.000	0.005	-0.005
	(1.58)	(-0.23)	(-0.06)	(1.15)	(-1.64)
Momentum	-0.003	0.210	0.033	0.026	-0.003
	(-0.05)	(0.82)	(8.08)	(7.04)	(-0.89)
Earnings-to-Price	-0.007	-0.060	0.000	0.000	0.001
	(-0.34)	(-0.72)	(0.60)	(0.42)	(0.64)
Lagged Dependent	0.179	0.076	-0.406	-0.365	0.263
	(3.79)	(2.83)	(-17.10)	(-13.32)	(8.73)
R^2_{Adj}	0.116	0.109	0.155	0.128	0.247
N	4063	3641	12389	12389	8608
Firm Fixed	Yes	Yes	Yes	Yes	Yes
Year Fixed	Yes	Yes	Yes	Yes	Yes
Frequency	Quarterly	Quarterly	Monthly	Monthly	Monthly

Table 6: Portfolio Returns

We report the annualized returns for the value-weighted portfolios using common stocks in the NYSE, Amex, and Nasdaq exchanges for firms based in the city of New York. Each month, quintile portfolios are formed by sorting individual stocks based on their previous month $\beta^{\Delta WIVOL}$. Quintile 5 (High) contains stocks with the highest $\beta^{\Delta WIVOL}$ during the previous month. Quintile 1 (Low) contains stocks with the lowest $\beta^{\Delta WIVOL}$ during the previous month. The bottom row (Low-High) reports the differences between portfolio 1 and portfolio 5. The columns report the betas, returns and abnormal returns (alphas). Column 1 reports the average $\beta^{\Delta WIVOL}$ per quintile. Column 2 reports the raw excess returns. Column 3 reports the abnormal returns α_{MKT} controlling for the market factor MKT. Column 4 reports the abnormal returns α_{FF3} controlling for the three factors in Fama and French (1993). Column 5 reports the abnormal returns α_{C4} controlling for the three factors in Fama and French (1993) and the Carhart (1997) factor. Column 6 reports abnormal returns α_{FF5} controlling for the five factors in Fama and French (2015). Column 7 reports abnormal returns α_{HXZ4} controlling for the four factors in Hou, Xue and Zhang (2014). We report in parentheses the Newey-West corrected t-statistics. The sample period is from January 2008 to July 2021.

	$\beta^{\Delta WIVOL}$	Return	α_{MKT}	α_{FF3}	α_{C4}	α_{FF5}	α_{HXZ4}
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
High	0.29	2.88	2.16	1.44	0.72	1.92	0.72
		(0.55)	(0.33)	(0.19)	(0.10)	(0.26)	(0.09)
Q4	0.03	6.84	5.52	3.84	3.48	3.72	2.88
		(1.44)	(0.96)	(0.61)	(0.51)	(0.59)	(0.43)
Q3	-0.03	4.92	4.08	1.92	2.04	2.52	2.64
		(0.93)	(0.79)	(0.34)	(0.34)	(0.45)	(0.44)
Q2	-0.09	13.56	12.60	11.16	10.92	10.92	9.96
		(2.80)	(3.02)	(2.45)	(2.34)	(2.43)	(2.33)
Low	-0.37	11.64	10.68	9.12	8.76	10.08	9.84
		(2.25)	(1.89)	(1.45)	(1.38)	(1.51)	(1.52)
Low-High		8.76	8.52	7.68	8.04	8.04	9.12
		(2.44)	(2.32)	(2.01)	(2.05)	(2.13)	(2.28)

Table 7: Firm-level WIVOL Exposure and Return Predictability

We report the Fama-MacBeth cross-sectional regressions using common stocks in the NYSE, Amex, and Nasdaq exchanges for firms based in the city of New York. The dependent variable is the firm's monthly stock return. Column 1 reports the univariate regression using the benchmark explanatory variable, $\beta^{\Delta WIVOL}$, the firm's exposure to weather volatility. Columns 2 to 8 incrementally control for firm-level size (market capitalization), cashflow (cash holdings over assets), gross profitability (Novy-Marx (2013)), market leverage, investment (capital expenditures over lagged assets), book to market ratio and Altman's Z-score. All explanatory variables are one-period lagged. We report in parentheses the Newey-West corrected t-statistics. The sample period is from January 2008 to July 2021.

Dependent Variable	Firm Return							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Intercept	0.66	0.65	1.98	1.87	1.90	1.86	1.29	1.75
	(1.94)	(2.39)	(2.77)	(2.74)	(2.91)	(3.17)	(1.91)	(1.83)
$\beta^{\Delta WIVOL}$	-1.47	-1.45	-1.32	-1.25	-1.16	-1.11	-1.15	-1.30
	(-2.59)	(-2.65)	(-2.19)	(-2.14)	(-2.08)	(-2.05)	(-2.22)	(-2.20)
Size		0.00	-0.14	-0.15	-0.15	-0.16	-0.12	-0.18
		(0.06)	(-2.83)	(-2.75)	(-2.75)	(-2.99)	(-2.36)	(-2.14)
Cashflow			1.11	1.02	0.96	1.01	1.19	1.65
			(1.96)	(1.73)	(1.85)	(2.04)	(2.41)	(3.03)
Profitability				2.60	2.65	2.87	3.66	2.19
				(1.83)	(1.74)	(1.83)	(2.00)	(1.18)
Leverage					-0.01	0.06	-0.25	0.42
					(-0.02)	(0.12)	(-0.50)	(0.52)
Investment						2.57	2.98	2.83
						(0.79)	(0.92)	(0.71)
Book-to-market							0.41	0.14
							(1.58)	(0.46)
Z-score								0.02
								(0.37)
R^2_{Adj}	0.02	0.03	0.04	0.05	0.05	0.06	0.07	0.10
N	86,726	86,726	86,726	86,726	86,726	86,726	86,726	86,726

Table 8: Information Friction and Return Predictability

We report the annualized returns from independent double sorts between firms' WIVOL beta and alternative firms' characteristics. For each lagged firm-level characteristic, the columns group above median (High) and below median (Low) firms. The rows then group firms with the previous month most positive WIVOL beta quintile (High) and most negative WIVOL beta quintile (Low). The bottom rows report the returns from the long-short (Low minus High) WIVOL beta strategy and the the intercept from the long-short stategy onto the market factor. Columns 1 and 2 group stocks based on institutional ownership over shares outstanding. Columns 3 and 4 group based on hedge fund ownership over shares outstanding as per Merton (1987). Columns 5 and 6 group based on the ownership concentration measured by the Herfindahl index of ownership. Columns 7 and 8 group based on the number of institutional owners situated in the same country (the United States) as in Baik, Kang, and Kim (2010). Columns 9 and 10 group based the number of institutional owners situated in the same city (New York) as in Bernile, Kumar, and Sulaeman (2015). All five ownership variables are orthogonalized with respect to the firm size and the information about firm level institutional holdings is sourced from the FactSet Ownership database. We report in parentheses the Newey-West corrected t-statistics. The sample period is from January 2008 to July 2021.

	Institutional		Hedge Fund		Herfindahl		Domestic		City	
	High	Low	High	Low	High	Low	High	Low	High	Low
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
High	13.87	1.24	9.71	4.89	3.17	15.78	0.68	13.83	4.87	6.88
	(2.18)	(0.20)	(1.50)	(0.80)	(0.54)	(2.24)	(0.11)	(2.21)	(0.76)	(1.12)
Low	8.85	18.24	11.36	14.21	15.04	9.91	14.65	10.14	15.05	11.42
	(1.41)	(3.04)	(1.83)	(2.47)	(2.65)	(1.52)	(2.57)	(1.62)	(2.50)	(1.91)
Low - High	-5.02	17.01	1.65	9.32	11.88	-5.87	13.98	-3.68	10.17	4.55
	(-1.09)	(3.40)	(0.35)	(2.01)	(2.84)	(-1.22)	(2.79)	(-0.84)	(2.09)	(0.86)
α_{MKT}	-5.06	17.12	1.66	9.83	11.82	-5.06	13.51	-2.90	10.01	5.80
	(-1.11)	(3.61)	(0.29)	(2.22)	(2.86)	(-1.07)	(2.57)	(-0.70)	(2.18)	(1.22)

Table 9: Local Exposure, Profitability, and Return Predictability

We report the annualized returns from independent double sorts between firms' WIVOL beta and alternative firms' characteristics. For each lagged firm-level characteristic, the columns group above median (High) and below median (Low) firms. The rows then group firms with the previous month most positive WIVOL beta quintile (High) and most negative WIVOL beta quintile (Low). The bottom rows report the returns from the long-short (Low minus High) WIVOL beta strategy and the the intercept from the long-short stategy onto the market factor. Columns 1 and 2 group firms based on the local operational presence, measured by the number of employees in the same state from National Establishment Time-Series (NETS) Database. Columns 3 and 4 group based on the reliance on labor productivity growth as a source of income, measured by the growth rate of sales per employee. Columns 5 and 6 group based on firms' equity duration as in Dechow, Sloan, and Soliman (2004). Columns 7 and 8 group based on operating profit, defined as revenue minus cost minus administrative expenses minus interest expenses, scaled by book value of equity . Columns 9 and 10 group based on return on assets, calculated as net income over book value of assets. Columns 11 and 12 group based on the firm size, the market capitalization. We report in parentheses the Newey-West corrected t-statistics. The sample period is from January 2008 to July 2021.

	Employment		Productivity		Equity Duration		Profitability		ROA		Size	
	High	Low	High	Low	High	Low	High	Low	High	Low	High	Low
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
High	3.13	7.28	5.16	10.47	7.55	6.52	2.16	5.29	6.28	10.22	2.81	17.37
	(0.46)	(1.26)	(0.79)	(1.64)	(1.09)	(1.04)	(0.39)	(0.73)	(1.04)	(1.35)	(0.48)	(2.38)
Low	14.51	12.92	20.83	8.65	19.49	11.11	11.98	9.41	15.24	15.69	12.73	20.48
	(2.30)	(2.08)	(2.55)	(1.48)	(2.49)	(2.05)	(1.93)	(1.46)	(3.01)	(1.40)	(2.32)	(2.66)
Low - High	11.37	5.64	15.67	-1.82	11.94	4.60	9.82	4.12	8.97	5.47	9.92	3.11
	(1.98)	(1.20)	(1.97)	(-0.35)	(1.72)	(1.13)	(1.77)	(0.65)	(2.07)	(0.56)	(2.56)	(0.45)
α_{MKT}	11.84	5.26	15.90	-0.96	12.24	3.76	10.72	4.93	9.97	3.23	9.57	5.38
	(2.14)	(1.13)	(2.07)	(-0.16)	(2.00)	(0.82)	(1.97)	(0.77)	(2.33)	(0.30)	(2.68)	(0.89)

Table 10: Exposure to Foreign Weather and Return Predictability

We report the annualized returns for the value-weighted portfolios using common stocks in the NYSE, Amex, and Nasdaq exchanges. Panel A estimates the exposure of firms based in the city of New York with respect to ΔWIVOL for the metro area of Dallas Fort-Worth. Panel B estimates the exposure of firms based in the metro area of Dallas Fort-Worth with respect to ΔWIVOL for the city of New York. Quintile 5 (High) contains stocks with the highest $\beta^{\Delta WIVOL}$ during the previous month. Quintile 1 (Low) contains stocks with the lowest $\beta^{\Delta WIVOL}$ during the previous month. The bottom row (Low-High) reports the differences between portfolio 1 and portfolio 5. The columns report the betas, returns and abnormal returns (alphas). Column 1 reports the average $\beta^{\Delta WIVOL}$ per quintile. Column 2 reports the raw excess returns. Column 3 reports the abnormal returns α_{MKT} controlling for the market factor MKT. Column 4 reports the abnormal returns α_{FF3} controlling for the three factors in Fama and French (1993). Column 5 reports the abnormal returns α_{C4} controlling for the three factors in Fama and French (1993) and the Carhart (1997) factor. Column 6 reports abnormal returns α_{FF5} controlling for the five factors in Fama and French (2015). Column 7 reports abnormal returns α_{HXZ4} controlling for the four factors in Hou, Xue and Zhang (2014). We report in parentheses the Newey-West corrected t-statistics. The sample period is from January 2008 to July 2021.

	$\beta^{\Delta WIVOL}$ (1)	Return (2)	α_{MKT} (3)	α_{FF3} (4)	α_{C4} (5)	α_{FF5} (6)	α_{HXZ4} (7)
Panel A. New York firms exposure to Dallas Fort-Worth ΔWIVOL							
High	0.21	5.88	5.28	5.28	5.40	5.28	5.16
		(3.28)	(2.64)	(2.56)	(2.70)	(2.46)	(2.40)
Low	-0.18	5.04	4.68	4.44	4.32	4.56	4.20
		(2.98)	(3.21)	(2.69)	(2.52)	(2.72)	(2.43)
Low-High		-0.84	-0.72	-0.84	-1.08	-0.72	-0.96
		(-0.45)	(-0.35)	(-0.36)	(-0.51)	(-0.29)	(-0.41)
Panel B. Dallas Fort-Worth firms exposure to New York ΔWIVOL							
High	0.40	5.52	5.76	5.52	6.24	5.64	6.00
		(3.04)	(3.24)	(2.95)	(3.08)	(2.69)	(2.91)
Low	-0.38	5.28	5.16	5.16	5.04	4.92	4.56
		(2.95)	(2.80)	(2.72)	(2.72)	(2.69)	(2.38)
Low-High		-0.24	-0.48	-0.36	-1.20	-0.60	-1.44
		(-0.09)	(-0.24)	(-0.16)	(-0.53)	(-0.26)	(-0.59)

Table A.1: WIVOL and Fundamentals: Sector Effect

We report the effect of the weather implied volatility on the firms' fundamental levels and uncertainties using panel regressions. The dependent variables are the logarithm values and the absolute quarterly change values the following variables: the cost of goods sold ($ln(COGS)$ and $|\Delta$COGS$|$), the selling, general and administrative expense ($ln(XSGA)$ and $|\Delta$XSGA$|$), the total operating expense ($ln(XOPR)$) and $|\Delta$XOPR$|$, the firms' revenue ($ln(SALES)$ and $|\Delta$SALES$|$). The absolute change values are scaled by the last quarter's total asset. The main explanatory variable is $\Delta WIVOL$, the changes in the weather option implied volatility. All regressions include the sector dummy, the interaction term between the sector dummy and $\Delta WIVOL$ (i_Sector), lagged dependant variable and all other control variables described in Table 3 and 4 of the paper. We report in parentheses the t-statistics controlling for firm and year fixed effects and clustering standard errors at the firm level.

Dependent Variable	$ln(COGS)$						$ln(XSGA)$					
Sector Dummy	Manuf	Transp	Whole	Retail	Finance	Service	Manuf	Transp	Whole	Retail	Finance	Service
$\Delta WIVOL$	0.023	0.061	0.050	0.064	0.065	0.063	0.030	0.059	0.069	0.085	0.077	0.081
	(0.89)	(2.14)	(1.92)	(2.34)	(2.10)	(2.22)	(1.26)	(2.36)	(2.91)	(3.34)	(3.06)	(3.13)
i_Sector	0.145	-0.063	0.074	-0.109	-0.041	-0.056	0.134	0.058	0.007	-0.116	-0.106	-0.060
	(2.29)	(-1.37)	(0.82)	(-1.92)	(-0.74)	(-1.17)	(2.87)	(0.92)	(0.10)	(-3.64)	(-2.35)	(-1.24)

	$ln(XOPR)$						$ln(SALES)$					
	Manuf	Transp	Whole	Retail	Finance	Service	Manuf	Transp	Whole	Retail	Finance	Service
$\Delta WIVOL$	0.040	0.048	0.061	0.074	0.084	0.075	-0.018	0.015	0.017	0.022	0.046	0.024
	(1.34)	(1.94)	(2.24)	(2.59)	(2.58)	(2.49)	(-0.73)	(0.53)	(0.66)	(0.82)	(1.61)	(0.87)
i_Sector	0.108	0.107	0.061	-0.113	-0.070	-0.075	0.164	0.022	0.029	-0.041	-0.096	-0.038
	(1.99)	(0.95)	(0.88)	(-2.28)	(-1.21)	(-1.68)	(2.97)	(0.75)	(0.33)	(-0.89)	(-1.90)	(-0.87)

	$\|\Delta$COGS$\|$						$\|\Delta$XSGA$\|$					
	Manuf	Transp	Whole	Retail	Finance	Service	Manuf	Transp	Whole	Retail	Finance	Service
$\Delta WIVOL$	0.010	0.018	0.015	0.016	0.011	0.018	0.002	0.003	0.003	0.003	0.002	0.002
	(1.49)	(2.26)	(2.07)	(2.07)	(1.64)	(2.24)	(1.26)	(2.06)	(1.66)	(1.73)	(1.51)	(1.37)
i_Sector	0.022	-0.021	-0.005	-0.007	0.013	-0.019	0.002	-0.006	-0.004	-0.002	0.001	0.004
	(1.06)	(-2.75)	(-0.33)	(-0.83)	(0.87)	(-2.24)	(1.00)	(-2.81)	(-0.60)	(-0.67)	(0.35)	(1.11)

	$\|\Delta$XOPR$\|$						$\|\Delta$SALES$\|$					
	Manuf	Transp	Whole	Retail	Finance	Service	Manuf	Transp	Whole	Retail	Finance	Service
$\Delta WIVOL$	0.011	0.019	0.016	0.017	0.012	0.018	0.011	0.020	0.018	0.019	0.015	0.020
	(1.63)	(2.41)	(2.18)	(2.18)	(1.72)	(2.24)	(1.49)	(2.30)	(2.22)	(2.25)	(1.88)	(2.21)
i_Sector	0.021	-0.025	-0.007	-0.008	0.013	-0.015	0.029	-0.020	-0.016	-0.014	0.010	-0.015
	(1.00)	(-3.03)	(-0.37)	(-0.73)	(0.86)	(-1.62)	(1.26)	(-2.27)	(-0.81)	(-0.87)	(0.59)	(-1.37)

Table A.2: Estimation Robustness: Portfolio Returns

We report the annualized returns for the value-weighted portfolios using common stocks in the NYSE, Amex, and Nasdaq exchanges for firms based in the city of New York. Each month, quintile portfolios are formed by sorting individual stocks based on their previous month $\beta^{\Delta WIVOL}$. Each firm's beta is estimated using alternative controls specifications in the estimation of equation (5.1). In Panel A, $\beta^{\Delta WIVOL}$ is estimated with no controls (specification 1). In Panel B, $\beta^{\Delta WIVOL}$ is estimated controlling for the market factor MKT (specification 2). In Panel C, $\beta^{\Delta WIVOL}$ is estimated controlling for the historical weather volatility (specification 3). In each panel, Quintile 5 contains stocks with the highest $\beta^{\Delta WIVOL}$ during the previous month. Quintile 1 contains stocks with the lowest $\beta^{\Delta WIVOL}$ during the previous month. The bottom row reports the returns from the long-short (Low - High) strategy, which buys stocks with most negative betas and sells stocks with most positive betas. The columns report the betas, returns and abnormal returns (alphas). Column 1 reports the average $\beta^{\Delta WIVOL}$ per quintile. Column 2 reports the raw excess returns. Column 3 reports the abnormal returns α_{MKT} controlling for the market factor MKT. Column 4 reports the abnormal returns α_{FF3} controlling for the three factors in Fama and French (1993). Column 5 reports the abnormal returns α_{C4} controlling for the three factors in Fama and French (1993) and the Carhart (1997) factor. Column 6 reports abnormal returns α_{FF5} controlling for the five factors in Fama and French (2015). Column 7 reports abnormal returns α_{HXZ4} controlling for the four factors in Hou, Xue and Zhang (2014). We report in parentheses the Newey-West corrected t-statistics. The sample period is from January 2008 to July 2021.

	$\beta^{\Delta WIVOL}$ (1)	Return (2)	α_{MKT} (3)	α_{FF3} (4)	α_{C4} (5)	α_{FF5} (6)	α_{HXZ4} (7)
Panel A. WIVOL beta specification 1							
High	0.22	3.96	2.88	2.28	1.56	2.52	1.08
		(0.81)	(0.50)	(0.36)	(0.23)	(0.38)	(0.17)
Low	-0.41	13.08	12.24	10.80	10.44	11.76	11.16
		(2.36)	(2.09)	(1.67)	(1.60)	(1.74)	(1.72)
Low-High		9.12	9.36	8.52	8.88	9.12	9.96
		(2.34)	(2.49)	(2.14)	(2.20)	(2.38)	(2.55)
Panel B. WIVOL beta specification 2							
High	0.31	2.52	1.68	0.60	0.00	1.20	-0.36
		(0.46)	(0.26)	(0.08)	(0.00)	(0.16)	(-0.06)
Low	-0.38	11.40	10.44	8.76	8.28	9.84	9.00
		(1.95)	(1.62)	(1.24)	(1.15)	(1.32)	(1.27)
Low-High		8.88	8.76	8.16	8.28	8.64	9.48
		(2.18)	(2.11)	(1.91)	(1.92)	(2.03)	(2.21)
Panel C. WIVOL beta specification 3							
High	0.26	4.08	2.76	2.52	1.32	2.88	0.00
		(0.86)	(0.51)	(0.41)	(0.21)	(0.45)	(0.00)
Low	-0.43	12.72	11.76	10.08	9.72	11.28	10.56
		(2.33)	(2.02)	(1.57)	(1.49)	(1.69)	(1.63)
Low-High		8.64	9.00	7.56	8.40	8.52	10.56
		(2.26)	(2.60)	(2.04)	(2.22)	(2.31)	(2.87)

Table A.3: Estimation Robustness: Firm-level Exposure and Return Predictability

We report the Fama-MacBeth cross-sectional regressions using common stocks in the NYSE, Amex, and Nasdaq exchanges for firms based in the city of New York. The dependent variable is the firm's monthly stock return. The main explanatory is the firm's exposure to innovation in weather volatility risk $\beta^{\Delta WIVOL}$. Each firm's beta is estimated using alternative controls specifications in the estimation of equation (5.1). In columns 1 and 2, $\beta^{\Delta WIVOL}$ is estimated with no controls. In columns 3 and 4, $\beta^{\Delta WIVOL}$ is estimated controlling for the market factor MKT. In columns 5 and 6, $\beta^{\Delta WIVOL}$ is estimated controlling for the historical weather volatility. All explanatory variables are one-period lagged. We report in parentheses the Newey-West corrected t-statistics. The sample period is from January 2008 to July 2021.

Dependent Variable	Firm Return					
	(1)	(2)	(3)	(4)	(5)	(6)
Intercept	0.59	0.55	0.66	0.66	0.58	0.59
	(2.15)	(2.35)	(1.93)	(2.40)	(1.84)	(2.27)
$\beta^{\Delta WIVOL}$	-1.65	-1.64	-1.43	-1.42	-1.54	-1.58
	(-2.01)	(-2.06)	(-2.38)	(-2.43)	(-2.32)	(-2.42)
Size		0.01		0.00		0.00
		(0.16)		(0.04)		(-0.02)
R^2_{Adj}	0.04	0.05	0.03	0.04	0.04	0.05
N	108,426	108,426	108,426	108,426	108,426	108,426

Table A.4: Portfolio Returns (Non-Financials)

We report the annualized returns for the value-weighted portfolios using common stocks in the NYSE, Amex, and Nasdaq exchanges for firms based in the city of New York. The sample exclude firms in the financial sector based on the firm's SIC code (60-67 Finance, Insurance, Real Estate). Each month, quintile portfolios are formed by sorting individual stocks based on their previous month $\beta^{\Delta WIVOL}$. Quintile 5 (High) contains stocks with the highest $\beta^{\Delta WIVOL}$ during the previous month. Quintile 1 (Low) contains stocks with the lowest $\beta^{\Delta WIVOL}$ during the previous month. The bottom row (Low-High) reports the differences between portfolio 1 and portfolio 5. The columns report the betas, returns and abnormal returns (alphas). Column 1 reports the average $\beta^{\Delta WIVOL}$ per quintile. Column 2 reports the raw excess returns. Column 3 reports the abnormal returns α_{MKT} controlling for the market factor MKT. Column 4 reports the abnormal returns α_{FF3} controlling for the three factors in Fama and French (1993). Column 5 reports the abnormal returns α_{C4} controlling for the three factors in Fama and French (1993) and the Carhart (1997) factor. Column 6 reports abnormal returns α_{FF5} controlling for the five factors in Fama and French (2015). Column 7 reports abnormal returns α_{HXZ4} controlling for the four factors in Hou, Xue and Zhang (2014). We report in parentheses the Newey-West corrected t-statistics. The sample period is from January 2008 to July 2021.

	$\beta^{\Delta WIVOL}$	Return	α_{MKT}	α_{FF3}	α_{C4}	α_{FF5}	α_{HXZ4}
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
High	0.51	5.64	4.08	0.96	0.60	2.40	1.08
		(0.75)	(0.54)	(0.11)	(0.08)	(0.28)	(0.13)
Q4	0.10	10.08	8.88	8.40	7.68	7.80	6.36
		(1.99)	(1.85)	(1.63)	(1.45)	(1.44)	(1.20)
Q3	-0.01	15.60	14.76	13.92	13.80	15.48	12.84
		(2.84)	(2.61)	(2.20)	(2.10)	(2.39)	(2.14)
Q2	-0.13	8.04	6.72	5.40	4.68	4.08	3.36
		(1.49)	(1.10)	(0.81)	(0.68)	(0.57)	(0.46)
Low	-0.57	18.00	17.28	16.32	16.44	16.80	15.60
		(2.16)	(2.20)	(1.93)	(1.89)	(1.86)	(1.77)
Low-High		12.36	13.20	15.36	15.84	14.28	14.52
		(1.91)	(2.79)	(3.02)	(3.07)	(2.68)	(2.97)

Table A.5: Portfolio Returns (Radius 100)

We report the annualized returns for the value-weighted portfolios using common stocks in the NYSE, Amex, and Nasdaq exchanges. The sample includes firms with headquarters within 100 miles from the LaGuardia airport. Each month, quintile portfolios are formed by sorting individual stocks based on their previous month $\beta^{\Delta WIVOL}$. Quintile 5 (High) contains stocks with the highest $\beta^{\Delta WIVOL}$ during the previous month. Quintile 1 (Low) contains stocks with the lowest $\beta^{\Delta WIVOL}$ during the previous month. The bottom row (Low-High) reports the differences between portfolio 1 and portfolio 5. The columns report the betas, returns and abnormal returns (alphas). Column 1 reports the average $\beta^{\Delta WIVOL}$ per quintile. Column 2 reports the raw excess returns. Column 3 reports the abnormal returns α_{MKT} controlling for the market factor MKT. Column 4 reports the abnormal returns α_{FF3} controlling for the three factors in Fama and French (1993). Column 5 reports the abnormal returns α_{C4} controlling for the three factors in Fama and French (1993) and the Carhart (1997) factor. Column 6 reports abnormal returns α_{FF5} controlling for the five factors in Fama and French (2015). Column 7 reports abnormal returns α_{HXZ4} controlling for the four factors in Hou, Xue and Zhang (2014). We report in parentheses the Newey-West corrected t-statistics. The sample period is from January 2008 to July 2021.

	$\beta^{\Delta WIVOL}$	Return	α_{MKT}	α_{FF3}	α_{C4}	α_{FF5}	α_{HXZ4}
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
High	0.87	6.96	6.72	5.88	5.52	6.72	5.16
		(1.49)	(1.21)	(0.95)	(0.85)	(1.07)	(0.80)
Q4	0.06	8.88	8.04	7.32	7.44	8.40	7.44
		(1.96)	(1.64)	(1.34)	(1.31)	(1.49)	(1.37)
Q3	-0.02	11.04	9.96	8.88	7.92	9.00	7.56
		(2.37)	(2.09)	(1.66)	(1.46)	(1.63)	(1.48)
Q2	-0.10	8.28	7.56	6.84	6.60	7.20	6.60
		(1.78)	(1.55)	(1.27)	(1.18)	(1.28)	(1.18)
Low	-0.94	23.28	22.08	18.24	17.28	20.52	19.44
		(2.68)	(2.42)	(2.20)	(2.25)	(2.26)	(2.31)
Low-High		16.32	15.36	12.36	11.76	13.92	14.28
		(2.15)	(2.23)	(2.27)	(2.57)	(2.18)	(2.56)

Table A.6: Portfolio Returns and Exposure to Temperature Shocks

We report the annualized returns for the value-weighted portfolios using common stocks in the NYSE, Amex, and Nasdaq exchanges for firms based in the city of New York. Each month, quintile portfolios are formed by sorting individual stocks based on their previous month β^*. Each firm's beta is estimated using alternative controls specifications in the estimation of equation (5.1). In Panel A, β^* is estimated using the percentage change in CMIP temperature forecasts. In Panel B, β^* is estimated using the percentage change in NOAA temperatures. In Panel C, β^* is estimated using CME monthly weather futures returns. In each panel, Quintile 5 contains stocks with the highest β^* during the previous month. Quintile 1 contains stocks with the lowest β^* during the previous month. The bottom row reports the returns from the long-short (Low - High) strategy, which buys stocks with most negative betas and sells stocks with most positive betas. The columns report the betas, returns and abnormal returns (alphas). Column 1 reports the average β per quintile. Column 2 reports the raw excess returns. Column 3 reports the abnormal returns α_{MKT} controlling for the market factor MKT. Column 4 reports the abnormal returns α_{FF3} controlling for the three factors in Fama and French (1993). Column 5 reports the abnormal returns α_{C4} controlling for the three factors in Fama and French (1993) and the Carhart (1997) factor. Column 6 reports abnormal returns α_{FF5} controlling for the five factors in Fama and French (2015). Column 7 reports abnormal returns α_{HXZ4} controlling for the four factors in Hou, Xue and Zhang (2014). We report in parentheses the Newey-West corrected t-statistics. The sample period is from January 2008 to July 2021.

	β^*	Return	α_{MKT}	α_{FF3}	α_{C4}	α_{FF5}	α_{HXZ4}
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A. Estimation of Beta w.r.t. temp. forecasts							
High	0.35	5.04	3.60	1.68	1.32	1.32	1.08
		(0.88)	(0.56)	(0.25)	(0.18)	(0.18)	(0.14)
Low	-0.39	9.84	8.64	7.68	7.08	8.88	6.84
		(1.87)	(1.47)	(1.18)	(1.07)	(1.31)	(1.09)
Low-High		4.80	4.92	6.00	5.88	7.56	5.88
		(1.09)	(1.15)	(1.34)	(1.29)	(1.63)	(1.22)
Panel B. Estimation of Beta w.r.t. historical temp.							
High	1.17	7.92	7.20	5.76	5.28	6.24	5.28
		(1.51)	(1.42)	(0.99)	(0.86)	(1.03)	(0.85)
Low	-1.18	14.52	13.92	13.44	12.84	14.40	13.08
		(2.57)	(2.09)	(1.81)	(1.73)	(1.90)	(1.90)
Low-High		6.60	6.72	7.56	7.56	8.04	7.80
		(1.57)	(1.64)	(1.61)	(1.62)	(1.70)	(1.82)
Panel C. Estimation of Beta w.r.t. weather futures							
High	0.04	9.36	8.16	7.68	8.40	8.16	7.68
		(1.95)	(1.75)	(1.46)	(1.50)	(1.51)	(1.40)
Low	-0.04	6.60	6.00	4.32	2.76	5.88	4.80
		(1.15)	(0.96)	(0.60)	(0.38)	(0.82)	(0.71)
Low-High		-2.76	-2.16	-3.36	-5.64	-2.28	-2.88
		(-0.60)	(-0.53)	(-0.78)	(-1.36)	(-0.53)	(-0.68)

Table A.7: WIVOL Exposure, Characteristics and Industries

We report in Panel A firms' characteristics across beta sorted portfolios using common stocks in the NYSE, Amex, and Nasdaq exchanges for firms based in the city of New York. The panel reports the value-weighted average characteristic per portfolio quintile. Portfolios are sorted on the firm's weather volatility exposure, $\beta^{\Delta WIVOL}$. Columns 2 to 7 respectively report value-weighted quintile averages for cashflow in percent (cash holdings over assets), gross profitability (Novy-Marx (2013)), market leverage, investment in percent (capital expenditures over lagged assets), book to market ratio and Altman's Z-score. Panel B reports the average quintile $\beta^{\Delta WIVOL}$ using firms in alternative industries. The sample of firms is selected based on their SIC industry classification. Columns 1 to 6 report the average quintile $\beta^{\Delta WIVOL}$ for the manufacturing (SIC 20-39), transportation and public utilities (SIC 40-49), wholesale and retail trade (SIC 50-59), finance, insurance, real estate (SIC 60-67), services (SIC 70-89), and public administration (SIC 91-99) sectors.

Panel A. Characteristics across wivol exposures							
	$\beta^{\Delta WIVOL}$	Cashflow	Profitability	Leverage	Investment	BM	Z-score
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
High	0.29	0.14	4.94	0.35	1.25	0.53	0.40
Q4	0.03	0.12	3.49	0.38	1.05	0.56	0.21
Q3	-0.03	0.12	3.51	0.33	0.86	0.49	0.24
Q2	-0.09	0.12	4.76	0.31	1.04	0.45	0.39
Low	-0.37	0.15	5.38	0.33	1.06	0.54	0.40
Low-High		0.01	0.45	-0.03	-0.20	0.01	0.00
		(1.68)	(1.67)	(-1.58)	(-2.87)	(0.38)	(-0.10)

Panel B. Wivol exposure across industries						
	Manuf.	Transp.	Retail	Finance	Services	Admin.
	(1)	(2)	(3)	(4)	(5)	(6)
High	1.07	0.3	0.25	0.19	0.69	0.26
Q4	0.12	0.09	0.02	0.02	0.09	0.05
Q3	-0.03	0.01	-0.15	-0.03	-0.04	0.01
Q2	-0.18	-0.07	-0.29	-0.08	-0.18	-0.02
Low	-0.67	-0.3	-0.54	-0.27	-1.42	-0.1

Table A.8: Portfolio Returns (DFW)

We report the annualized returns for the value-weighted portfolios using common stocks in the NYSE, Amex, and Nasdaq exchanges for firms based in the metro area of Dallas Fort-Worth. Each month, quintile portfolios are formed by sorting individual stocks based on their previous month $\beta^{\Delta WIVOL}$. Quintile 5 (High) contains stocks with the highest $\beta^{\Delta WIVOL}$ during the previous month. Quintile 1 (Low) contains stocks with the lowest $\beta^{\Delta WIVOL}$ during the previous month. The bottom row (Low-High) reports the differences between portfolio 1 and portfolio 5. The columns report the betas, returns and abnormal returns (alphas). Column 1 reports the average $\beta^{\Delta WIVOL}$ per quintile. Column 2 reports the raw excess returns. Column 3 reports the abnormal returns α_{MKT} controlling for the market factor MKT. Column 4 reports the abnormal returns α_{FF3} controlling for the three factors in Fama and French (1993). Column 5 reports the abnormal returns α_{C4} controlling for the three factors in Fama and French (1993) and the Carhart (1997) factor. Column 6 reports abnormal returns α_{FF5} controlling for the five factors in Fama and French (2015). Column 7 reports abnormal returns α_{HXZ4} controlling for the four factors in Hou, Xue and Zhang (2014). We report in parentheses the Newey-West corrected t-statistics. The sample period is from January 2008 to July 2021.

	$\beta^{\Delta WIVOL}$	Return	α_{MKT}	α_{FF3}	α_{C4}	α_{FF5}	α_{HXZ4}
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
High	0.40	-0.12	-0.12	-0.60	-0.72	-0.12	-0.84
		(-0.07)	(-0.08)	(-0.35)	(-0.40)	(-0.05)	(-0.46)
Q4	0.10	6.12	5.76	5.76	6.24	6.24	6.60
		(3.12)	(2.83)	(2.74)	(3.00)	(2.90)	(3.07)
Q3	0.01	6.96	6.96	6.84	6.84	6.36	6.36
		(2.94)	(3.06)	(2.98)	(2.97)	(2.64)	(2.67)
Q2	-0.07	2.64	2.16	3.24	3.00	3.24	2.64
		(1.10)	(0.92)	(1.42)	(1.35)	(1.43)	(1.15)
Low	-0.34	3.48	3.12	3.12	3.24	3.96	3.84
		(1.88)	(1.94)	(2.00)	(2.04)	(2.48)	(2.16)
Low-High		3.60	3.24	3.72	3.96	4.08	4.80
		(2.02)	(1.98)	(2.01)	(2.14)	(2.15)	(2.45)

Table A.9: Firm-level Exposure and Return Predictability (DFW)

We report the Fama-MacBeth cross-sectional regressions using common stocks in the NYSE, Amex, and Nasdaq exchanges for firms based in the in the metro area of Dallas Fort-Worth. The dependent variable is the firm's monthly stock return. Column 1 reports the univariate regression using the benchmark explanatory variable, the firm's weather volatility exposure $\beta^{\Delta WIVOL}$. Column 2 controls for the firm's size defined as the log of the firm's market capitalization. All explanatory variables are one-period lagged. We report in parentheses the Newey-West corrected t-statistics. The sample period is from January 2008 to July 2021.

Dependent Variable	Firm Return	
	(1)	(2)
Intercept	0.12	-0.28
	(1.35)	(-3.66)
β^{WIVOL}	-0.28	-0.29
	(-2.07)	(-2.04)
Size		0.07
		(3.88)
R^2_{Adj}	0.02	0.04
N	17,959	17,959